WORKING paper

BANQUE DE FRANCE
EUROSYSTÈME

Innovation, Technology Standardization and the Value of the Firm

Antonin Bergeaud, Julia Schmidt & Riccardo Zago[1]

January 2026, WP #1031

Abstract

Technology standards are defined by national and international organizations to select and disseminate the best technologies and practices. Using a measure of patent quality and a novel measure of the semantic proximity between patents and standards documents, this paper exploits the standardization process to disentangle the respective contributions of innovation and diffusion to firm value. Producing a patent increases a firm's book value by 0.8% over the first eight years following the patent grant. However, this value deteriorates when the patent is not incorporated into a standard and diffused. In contrast, only firms whose patent specifications are included in a standard experience an additional increase in firm value of about 0.4% thereafter. Similar results are obtained when examining firms' market-value and net worth. Finally, by studying firm-level productivity and markups, we show that the value gains associated with innovation stem from productivity improvements, whereas those associated with diffusion arise from rent extraction.

Keywords: Standardization, Patents, Innovation, Firm Value.

JEL classification: G30; O31; O33.

[1] Contacts: Antonin Bergeaud: HEC Paris, CEP-LSE and CEPR (mailto:bergeaud@hec.fr); Julia Schmidt: Banque de France (mailto:julia.schmidt@banque-france.fr); Riccardo Zago: Banque de France (mailto:riccardo.zago@banque-france.fr). The authors want to thank without implicating Philippe Aghion, Simon Bunel, Michele Fioretti, Stéphane Guibaud, Valentin Haddad, Eric Mengus, Dimitris Papanikolaou, Jean-Guillaume Sahuc, Jean Tirole, Gianluca Violante and seminar participants at Banque de France, SED 2024, HEC Workshop on Firm Dynamics, Collège de France and INSEAD for helpful comments.

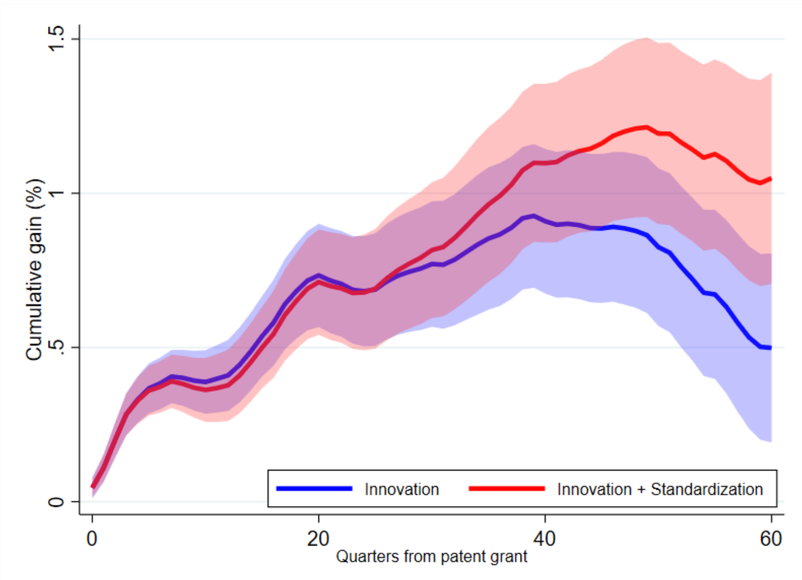
NON-TECHNICAL SUMMARY

Technology standards are fundamental to modern industrial societies, as they shape the development, production and widespread use of goods and services. Indeed, almost every technology we rely on a daily basis, from communication tools such as email and 5G to consumer devices and online payment systems, adheres to standards set by national or international standard-setting organizations, such as the International Organization for Standardization (ISO). These standards select certain technologies over others and promote their adoption, fostering interoperability among intermediate goods, reducing information frictions, guiding R&D, and ensuring product quality. As a result, they benefit both producers and consumers. Having a technology included in a standard is a major corporate event. Standardization governs the diffusion of technologies across an industry and provides a competitive advantage to firms that already possess the know-how and capabilities required to comply immediately with the standard. Consequently, the inclusion of a patent in a standard, and its ensuing distribution, contributes substantially to firm value beyond the value generated by innovation at the time a patent is granted.

By exploiting the grant date of patents, the publication date of standards, and a novel measure of the semantic proximity between patents and standards documents, this paper disentangles the respective contributions of innovation -the creation of new technologies- and diffusion -the adoption of these technologies through standardization- to firm value. While high-quality innovation immediately increases firm value, only firms whose patents are subsequently incorporated into a standard experience further increases in value in the long run. By contrast, firms whose patents are not included in standards see their value deteriorate over time.

Using a lead-lag framework to capture dynamic effects, this paper shows that patenting increases a firm's book value by approximately 0.8% over a ten-year horizon, rising to 1.2% when the patent becomes part of a standard, but declining when it does not (Figure 1 below). This highlights the central role of technological diffusion in sustaining firm value over time. Similar patterns emerge to firms' market value and leverage.

Figure 1. Long-run contribution of innovation and standardization to firm book-value



Note: This figure plots the dynamic effect of innovation (blue line) and the effect of diffusion (red line) when the patent is subsequently incorporated into a technology standard. On average, patents in a new standard are ten years old at the time of inclusion.

Finally, this paper shows that innovation primarily enhances firm productivity, whereas diffusion through standardization enables firms to temporarily extract higher markups and market rents. Overall, while innovation is essential for firm growth and value creation, diffusion driven by standardization is crucial for fully capitalizing on R&D investments, sustaining competitive advantage, and maximizing long-term firm value.

Innovation, normes technologiques et valeur de l'entreprise

Résumé

Les normes technologiques sont définies par des organisations nationales et internationales afin de sélectionner et de diffuser les meilleures technologies et pratiques. En mobilisant une mesure de la qualité des brevets ainsi qu'une nouvelle mesure de proximité sémantique entre les brevets et les documents de normes, cet article exploite le processus de standardisation pour distinguer les contributions respectives de l'innovation et de la diffusion à la valeur de l'entreprise. La création d'un brevet entraine une augmentation de 0.8% de la valeur comptable de l'entreprise au cours des huit premières années suivant son octroi. Toutefois, cet effet positif s'estompe lorsque le brevet n'est pas intégré à une norme et diffusé. A l'inverse, seules les entreprises dont les spécifications de brevets sont intégrées à une norme voient leur valeur augmenter de 0.4% supplémentaires par la suite. Des résultats similaires sont obtenus pour la valeur de marché de l'entreprise et sa valeur nette. Enfin, en analysant la productivité et les marges au niveau de l'entreprise, nous montrons que les gains de valeur associés à l'innovation proviennent de hausses de productivité, tandis que ceux liés à la diffusion résultent de l'extraction de rentes.

Mots-clés : normalisation, brevets, innovation, valeur de l'entreprise.

1 Introduction

Technology standards are pervasive in industrial societies and every sector heavily relies on them for the development and production of new goods and services. In fact, essentially all technologies that we use on a daily basis, from e-mails to a 5G connection, from a USB-c pen to online payments, have specifics that are defined by a standard. Standards are managed by national or international standard-setting organizations (SSOs), e.g. the International Standard Organization (ISO), which work for the definition and diffusion of the best practices and technology at the sectoral level. In this sense, technological standardization inherently involves the selection of one technology over competing ones and pushes for its widespread use. Therefore, through the definition of a common set of rules and specifications, SSOs do not only acknowledge high-quality innovations, but also want to stimulate spillovers and positive externalities. In fact, standards create a common technological field for all market participants, they give directions for future R&D, they reduce information frictions, they grant the interoperability of devices, compatibility of inputs and quality of products at the benefit of both producers and consumers.

In light of this, whether a firm sees its technology being included into a standard (or not) is extremely important as standardization rules the diffusion of that technology at the industry level and, consequently, can provide an additional competitive advantage to the firm with respect to direct competitors. This paper focuses on this particular corporate event to study to which extent technology diffusion –through the process of standardization– contributes to the value of the firm. By doing so, we can disentangle the different roles that innovation and diffusion play for a company and its growth from the moment a new technology is invented to the moment it becomes part of a standard and beyond. To our knowledge, this is the first paper that attempts to separate and quantify these two margins. The process of standardization is fundamental to do so as it allows to discretely split the life-cycle of a new technological patent into two periods: before the (eventual) inclusion of the patent into a standard, i.e. when the new technology is patented and enters in competition with existing ones; after standardization, when the technology is selected for diffusion and adoption at the industry level.

Conducting this analysis requires knowledge of i) the innovation output of the firm, and ii) to which extent each new innovation is included into a standard. For the former, we use patent data which is a widely used measure of innovation at the firm-level (see Hall et al., 2005). For the latter, we use documents approved by industry experts from SSOs that describe the basic features of the selected technology (known as *standards*). Prominent examples are mobile telecommunication standards (such as the 5G standard family) or Internet protocols. Then, we match the semantic content of (previously issued) patents to new standard documents such that we can express to what extent the content of a patent overlaps the content of the standard. In other words, this measure of semantic proximity tells how much the features of a technology patented by a firm are included in the new standard and –therefore– to which extent the new patented technology has the potential to diffuse since the publication of the related standards onwards. Once endowed with this patent-level measure, we aggregate it across the firm' patent portfolio and merge it with firm-level balance-sheet data along with data on the number of patents granted and their (forward) citations. This allows us to characterize in detail how the value of the firm responds i) to innovation activity, i.e. the release of a new patent; ii) innovation diffusion, i.e. the inclusion of the patent into a new standard.

Our results show that the release of a new promising patent –a patent that will be cited immediately more than others– has persistent positive effects on the firm's value. On the other hand, firms whose patents semantically align more with a newly released standard, i.e. patents whose underlying technology is featured in a new standard, have a positive but temporary increase in their value. This is consistent with Bergeaud et al. (2022), which show that firms whose patents are closer to a standard have a short-term competitive advantage as they own already the standardized technology which they can immediately deploy, scale and market while all other firms need to adjust in order to catch up. When looking at the cumulative effects of innovation and diffusion (through standardization), we find that the firm's value increases in the long run following the release of a patent. Yet, such increase deteriorates if the patent is not included into a standard and diffuse. Finally, we investigate what respectively innovation and diffusion stand for, and through which channels the two margins positively affect the value of the firm. Our results show that if on one side producing a promising technology leads to persistent firm-level productivity gains, it is through the diffusion of such technology that the firm is able to cash in its R&D efforts and to extract rent from the market by imposing higher markups. Also this effect is temporary, as firms far away from the standard reorganize and catch up to frontier firms throughout time.

In details, our analysis proceeds as follows. As patents and standards can be released in multiple consecutive periods and firms can publish a new patent while contemporaneously having older patents included in a new standard (and viceversa), first we use a dispersed lead-lag model with both margins of innovation activity and diffusion. In the spirit of Hall et al. (2005), this "horse-race" analysis between the two margins allows to identify the effect of patenting activity netting out the contemporaneous effect of standardization (and viceversa). Moreover, with respect to a static analysis, the lead-lag component allows to capture the full dynamics of the response following either the release of a new patent or a new standard. Under this empirical set-up, we find that firms that are granted a patent of high quality, i.e. that is cited more, gain more in terms of book and market-value and net-worth. This effect is not anticipated (or anticipated just by one quarter) and lasts on average more than one year. Conversely, firms whose technology becomes part of a standard see their book and market-value and net-worth increasing just for few quarters. The increase is higher the more the firm's technologies are included in the standard, i.e. the higher is our semantic measure of technological proximity. This result is important as it provides evidence that, despite the (scientific) quality of a patent being always observable by SSOs, the inclusion of a new technology into a standard discloses new information (beyond quality). In particular, it defines a competitive advantage for owners of the standardized technology as they can immediately scale and deploy their know-how while all other industry participants have to adjust. Hence, the diffusion process through standards contributes to the value of the firm. The role of diffusion significantly differ from the role played by innovation and the invention of new and promising technologies.

Thereafter, as the quality of patents (as measured by citations) cannot be directly compared with our semantic measure, we use the lead-lag model simply with two dummies taking respectively value one in periods a new patent is issued and/or included in a new standard. Then, we estimate the model and study how the effects of innovation and standardization accumulate over time. We do so also by keeping into account the distribution of the conversion rate of patents into standards, i.e. we account for the number of quarters it takes for a patent to become a standard and its distribution across firms and over time. This allows to properly assess the cumulative effect of diffusion –through standardization– and to compare it with the effect of innovation while taking into account when the inclusion of the patent into a standard occurs. With respect to firms that do not innovate, a firm that is granted a patent sees its book-value increasing by roughly 1% in ten years. At this point in time, if the patent is included in a standard, the book-value of the firm increases even further up to 1.5% in the following five years. Conversely, if there is no conversion, the book-value of the firm deteriorates and decreases by 0.5 percentage points. Similar dynamics are found when considering the market-value and the net-worth of the firm as dependent variable.

In the final part of the paper, we investigate through which channels the value of the firm builds up following the release of a new patent and its inclusion into a standard. By using firm-level TFP gains and markups as dependent variables in our lead-lag model, we find that innovation activity leads to persistent productivity gains whereas diffusion does not. On the other hand, technological diffusion through standardization allows firms to charge temporarily higher markups and extract more rent from the market.

All in all, these results demonstrate that innovation is an important determinant of the value of the firm. Yet, it is not enough. In fact, diffusion –as explained by the standardization process in our empirical analysis– is key for the firm to continue growing and to maintain its value in the long-run.

Related literature. This paper relates to three different strands of the literature.

The first one is on the implications of innovation for the value of the firm. Here, the literature leverages on two alternative methods to measure innovation activity and to study its implication. For example works such as Chan et al. (1990), Szewczyk et al. (1996) and Eberhart et al. (2004) study the role of R&D expenditure and show that firms exhibit positive abnormal returns and higher share value when the management announces an unexpected R&D investment plan. Yet, R&D expenditure cannot accurately capture neither the quantity nor the quality of the output of innovation activity, but rather the corporate effort. For this reason, the second approach used in the literature looks directly at the output of innovation, in particular to patents issued and their quality. For example, Hall et al. (2005) show that patent citations capture well the quality and relevance of inventions such that markets react accordingly. Similar results are found in Kogan et al. (2017), Pakes (1985a), Nicholas (2008) and Austin (1993), who show that stock prices increase to the release of high-quality patents. In line with this literature, our paper exploits the date of patent granting and a measure of patent quality (forward citations) to study how the value of the firm changes following successful innovations. However, it separates from most of the literature –which looks at short-term effects– as it considers the long-run evolution of the value of the firm. By doing so, our paper provides evidence on how patent generates value over each single patent life-cycle phase: when it is released (birth), when it diffuses (take off), when it is surpassed by new ones (maturity). In this sense, our paper relates also to the literature on innovation and creative destruction (e.g., Romer, 1990; Aghion and Howitt, 1992; Grossman and Helpman, 1991) and the literature on the "s-curve" of technology diffusion (see Geroski, 2000 for a review).

As we exploit technology standards to study to which extent a patent has the potential to diffuse and the underlying technology to be adopted, the second strand of literature we refer to is on standardization. Technology standards have received much attention in the industrial organization (IO) literature (see Kindleberger, 1983 for an historical overview) which has identified the benefits of this mechanism. By allowing for interoperability, compatibility and network effects (Katz and Shapiro, 1985; Farrell and Saloner, 1985), lower transaction costs and the reduction of information asymmetries (Leland, 1979), standardization is especially important for the large-scale diffusion and deployment of inventions and technologies. Standard-setting organizations (SSOs) are fundamental in that process (Rysman and Simcoe, 2008) and play an essential role for the industry-wide adoption of new technologies, especially in the case of general-purpose technologies (Basu and Fernald, 2008; Jovanovic and Rousseau, 2005). This has macroeconomic implications. In fact, as shown in Bergeaud et al. (2022), in the short-run standards give a competitive advantage to those firms that own already the technologies selected for diffusion by the SSO. This advantage translates into an immediate temporary increase of sales and markets shares for firms whose portfolio is closer to the standard. Yet, in the long-run, due to spillovers, all other firms innovate more, catch up with industry leaders and surpass them. This mechanism generates growth at the sectoral level. By using the semantic proximity measure of patents to standards from Bergeaud et al. (2022), in this paper we are able to discern which patents have higher potential to diffuse and, by exploiting the date of release of the standard document, how the diffusion triggered by the process of standardization contributes to the value of the firm.

Finally, our work contributes to the literature on text-mining applied to the semantic analysis of patents and standards. Text mining methods are increasingly used in economics and in particular in innovation economics, notably for the analysis of patent data (see Abbas et al., 2014 for an overview). For example, the semantics of patent documents can be used to measure patent similarity (Arts et al., 2018; Kuhn et al., 2020), to select patents in specific technologies (Bergeaud and Verluise, 2022; Dechezleprêtre et al., 2021; Bloom et al., 2021), to classify patents (Bergeaud et al., 2017; Webb et al., 2018; Argente et al., 2020) or to measure the novelty of a patent (Kelly et al., 2021).

The paper is organized as follows: Section 2 briefly describes the institutional frameworks of standards and the data; Section 3 we explain our empirical strategy and provide results. Section 4 concludes.

2 Institutional Framework and Data

2.1 Standards in brief

A standard, similar to a patent, is a document that describes certain features of a product, a production process or a protocol. Contrary to patents that are filed by individual inventors or firms, standards are developed by standard-setting organizations (SSOs) which gather industry experts from both the private and public sector in working groups and technical committees. Well-known examples are international SSOs such as ISO (International Organization for Standardization), national standard bodies such as DIN (Deutsches Institut für Normung) or industry associations such as IEEE (Institute of Electrical and Electronics Engineers). Most standards are considered public goods and many SSOs are non-profit organizations. Requiring approval by all stakeholders involved in the development of standards, they are often called *consensus standards*.

Standards are not defined to merely recognize the quality of some specific innovation over others or to confirm whether a technology has already completely diffused. Conversely, their goal is to reduce information frictions and make industry participants aware that, if they all adopt a specific technology, they can benefit from efficiency gains, vertical and horizontal synergies, cost reduction as they can produce (intermediary) goods and services compatible with each-others. In this sense, the standardized technology is superior not only for its scientific and innovative content, but also for its interoperability, compatibility and scalability. In fact, the goal of SSO is not to reward only good innovators. This would increase the risk of monopolistic power, along with the threat of technological lock-in. Actually, SSOs want to clearly state what is the technological direction industry participants should take in order to create a common technological field everybody can start from and build upon. Therefore, the creation of the standard will stimulate adoption and spillover effects within the industry, with short and long-term positive effects for both technological leaders and followers as for the economic performance of the entire industry (see Bergeaud et al., 2022).

In light of this, if patents are the output of innovation activity, standards are formal mechanisms to foster the diffusion of those innovations that can generate more spillovers and synergies, and can open more market opportunities for industry participants. Therefore, the patents considered to become the foundation of a new standard are not only selected for their quality but also for the broader advantages they would lead if they diffuse.

2.2 Data

We use the same data and sample from Bergeaud et al. (2022) and we defer details to this work and to Appendix A. Here, we report only the necessary information on data construction.

Patents and standards data. From the `IFI CLAIMS` database, we obtain most of the information we need about patents. In particular, we extract the abstract, the technological field (through the International Patent Classification code, or IPC) and the filing date of the patent application. We consider patents filed between years 1980 and 2010. Then, we use text analysis to extract and store keywords from each patent' abstract. Hence, for each patent i, we form a set of k-grams i.e. a sequence of k keywords, and define the set $B(i)$.

For standards, we use the Searle Centre Database on Technology Standards and Standard Setting Organizations (see Baron and Spulber, 2018 for more details). This data is largely based on `Perinorm`, a bibliographical database of product standards whose purpose is to provide subscribers with basic information on the standard. Our database covers all types of standards for a large number of industrialized countries. `Perinorm` also contains keywords describing each standard, which we store. Hence, for each standard j, we form a set of k-grams i.e. a sequence of k keywords, and define the set $A(j)$. Therefore, a first indicative measure of proximity of patent i to standard j is given by the number of common k-gram, i.e. $|\mathcal{A}(j) \cap \mathcal{B}(i)|$.

Yet, this component does not take into account if some k-gram is more important than others in describing the content of patent i, i.e. if some k-gram is more frequently repeated in the abstract of patent i. For this we define as $n(l, i)$ the number of times k-gram $l \in |\mathcal{A}(j) \cap \mathcal{B}(i)|$ appears in $\mathcal{B}(i)$.

Moreover, k-grams may have different length. Hence, we want to keep into account the fact that k-grams with longer length better describe both a patent and a standard. Consequently, a longer k-gram common to both patent i and standard j is more informative than a shorter common k-gram. Hence, we define $s(l)$ as the length of the k-gram $l \in |\mathcal{A}(j) \cap \mathcal{B}(i)|$.

Finally, we want to take into account also the fact that some k-gram might be frequently used across standards and therefore some key-words, although common to both patent and standard, may result uninformative of the specificity of the standard. Hence, for each k-gram $l \in |\mathcal{A}(j) \cap \mathcal{B}(i)|$, we calculate the so-called *inverse document frequencies* ($\mathrm{IDF}(l)$), which will give more weight to infrequent keywords that are more likely to describe the specialty of a given standard.

In light of this, we define the patent-to-standard matching score as follows:[1]

$$\mathrm{Score}(i, j) = (|\mathcal{A}(j) \cap \mathcal{B}(i)|) \times \sum_{l \in \mathcal{A}(j)} \left(\frac{n(k, i)}{|\mathcal{B}(i)|} \right)^{\frac{s(l)}{2}} \mathrm{IDF}(l)$$

where the second element weights the common k-grams by taking into account their length, importance within a patent, specialty across standards and, consequently, helps to to quantify properly the match of common keywords.

For our econometric analysis, we restrict the sample to unmatched and matched patents that have been filed at least one year prior to the publication of the standard.[2] As reported in panel (A) of Table 1, we have roughly 64.5 million of patent-standards matches. Half of patents in the final sample do not match any standard. If the match occurs, the mean time lag between patent filing and following standard release is 10 years. On average, each patent matches 2.6 standards.

In Bergeaud et al. (2022), we show that the variable Score is meaningful as patents whose content overlaps more and better with a new standard (i.e. a patent with higher matching score) have higher economic value, are cited more and are more likely to be renewed.

Firm-level data We use the mapping provided by Kogan et al. (2017) to associate each patent to the Compustat firm that filed it. Given the mapping between patents

[1] See Appendix B.1.2 for further details and alternative measures.

[2] Considering patents filed one year prior the publication of the standards attenuates the problem of opportunistic "just-in-time" patenting (see Kang and Bekkers, 2015).

and standards, we can aggregate scores at the firm-quarter level by weighting the sum of patents' scores with the relative importance of each 3-digit IPC class in the firm's initial (pre-sample) stock of patents.[3] Formally, define J as the set of all IPC classes such that $j \in J$ is a specific IPC class, and call $\mathtt{Score}_{i,p,j,t}$ the score obtained by firm i when matching patent p that belongs to the IPC class j and was issued up to $t-4$ to a standard published at time t. Then, the weighted aggregation of scores over IPC classes can be seen as a measure of the proximity of firms to the new technology standard (defined by standard document released at t). Formally, we define the proximity as:

$$\mathtt{Tech.Prox}_{i,t} = \sum_{j \in J} \omega_{i,j,t_0} \sum_{p \in j} \mathtt{Score}_{i,p,j,t}$$

where ω_{i,j,t_0} is the firm i's share of patents in the IPC class j measured in t_0, i.e. before 1980. We do this weighting for two reasons: first, the weighting reduces the role of those patents in IPCs that are not at the core of the firm's research activity and technological field; second, computing the weights in a pre-sample periods reduces the problem of firm self-selection into a specific IPC, which they anticipate to become important for a potential standard at some point in time.

To sum up, the variable $\mathtt{Tech.Prox}_{i,t}$ is a firm-quarter level continuous variable expressing the (IPC-weighted) proximity of the stock of patents (accumulated until $t-4$) of a firm to the standard released in quarter t. This variable can be either equal to zero, if the patents of a firm do not map into a new standard, or positive. In this case, the larger the variable $\mathtt{Tech.Prox}_{i,t}$ the closer the firm's portfolio of patents to the newly released standard.[4] In Bergeaud et al. (2022), we show that the variable $\mathtt{Tech.Prox}$ is meaningful at the intensive margin, it is not explained by the quantity of innovation output (i.e. the stock of patent cumulated prior to the issuance of a new standard), it is not explained by membership of a firm in a SSO, it is not explained by lobbying or strategic patenting behavior, it is relevant for firms with either high or low innovation output, it is meaningful also when comparing firms filing patents in the same technological field.

By exploiting the mapping of Kogan et al. (2017), we also collect information on the number of patents issued by each firm every quarter, the number of quarterly citations and the time-lag between the period these patents are issued and the period they match with a standard. This give us knowledge on the timing, quantity and quality of the newly issued patent and the and the spell between the patenting date and the inclusion of the specifics of the patent into a standard.

From Compustat, we consider the following variables of interest: the book-value of the

[3] See Appendix B.2 for the definition of technology classes of patents.

[4] We normalize this measure by its standard deviation such that it ranges from 0 to over 6. It is equal to 0 for more than half of the sample. See Table 1 for more details.

Table 1: DESCRIPTIVE STATISTICS FOR THE FIRM-LEVEL DATA

	Mean	SD	p1	p5	p25	p50	p75	p95	p99	N
(A) Patent-level data										
Score	505.6	1,549.8	0.0	0.0	0.0	227.1	480.4	1,799.8	5,139.7	64,574,039
Time lag	10.1	7.7	0.0	0.0	4.0	8.0	15.0	26.0	32.0	46,347,363
(B) Firm-level data										
Tech.Prox	0.34	2.02	0.00	0.00	0.00	0.00	0.10	1.27	6.37	23,867
$\mathbb{I}$[Tech.Prox > 0]	0.48	0.49	0.00	0.00	0.00	0.00	1.00	1.00	1.00	23,867
Patents	16.88	60.15	0.00	0.00	0.00	2.00	10.00	78.00	250.00	23,867
$\mathbb{I}$[Patents > 0]	0.61	0.49	0.00	0.00	0.00	1.00	1.00	1.00	1.00	23,867
Cit.	0.70	1.45	0.00	0.00	0.00	0.35	0.91	2.45	6.04	23,867
Time Lag (ω)	42.15	20.72	7.80	15.55	26.56	38.05	54.60	80.80	102.00	23,867
Book-value (Billion$)	5.19	22.62	0.00	0.00	0.11	0.83	3.35	17.95	77.41	23,867
Mkt-value (Billion$)	11.72	40.09	0.00	0.02	0.23	1.64	7.07	49.88	178.82	23,867
Net-worth (Billion$)	2.65	7.41	0.00	0.00	0.09	0.57	2.02	11.73	35.01	23,867
Age (quarters)	99.10	49.92	21.00	21.00	53.00	110.00	137.00	171.00	181.00	23,867
Q	1.98	2.15	0.74	0.90	1.17	1.49	2.11	4.41	8.69	23,867
Leverage	0.19	0.15	0.00	0.00	0.06	0.17	0.27	0.45	0.65	23,867

Notes: Panel A reports patent-level descriptive statistics. The variable Score captures the semantic proximity of a patent to a standard (see Appendix B.1.2), while the time lag is the average number of years that take for a patent to be matched to a standard from the patent's grant date onwards. Panel B reports firm-level descriptive statistics. The variable Tech.Prox measures the proximity of the portfolio of patent of the firm to a newly issued standard. $\mathbb{I}$[Tech.Prox > 0] is a dummy that takes value one for positive values of the variable Tech.Prox. Patents is the number of patents issued in the same quarter and $\mathbb{I}$[Patents > 0] takes value one if a firm has been granted at least a patent in that quarter. Cit. is the number of forward citations received by the patents in the firm's portfolio. ω is the average time lag between patent grant and inclusion of the patent in a new standard across the portfolio of patents. The firm's book-value is the value of equity and short/long-term debt at the net of common preferred shares. The Firm's market-value is the value of the outstanding shares and short/long-term debt at the net of common preferred shares. The firm's net-worth is the difference between the value fo assets and liabilities. Age is the number of quarters the firm is active. Q is the q-value of investments, and is built as the value of liabilities plus the market value of common equity divided by the book value of assets. Leverage is debt over the book value of assets.

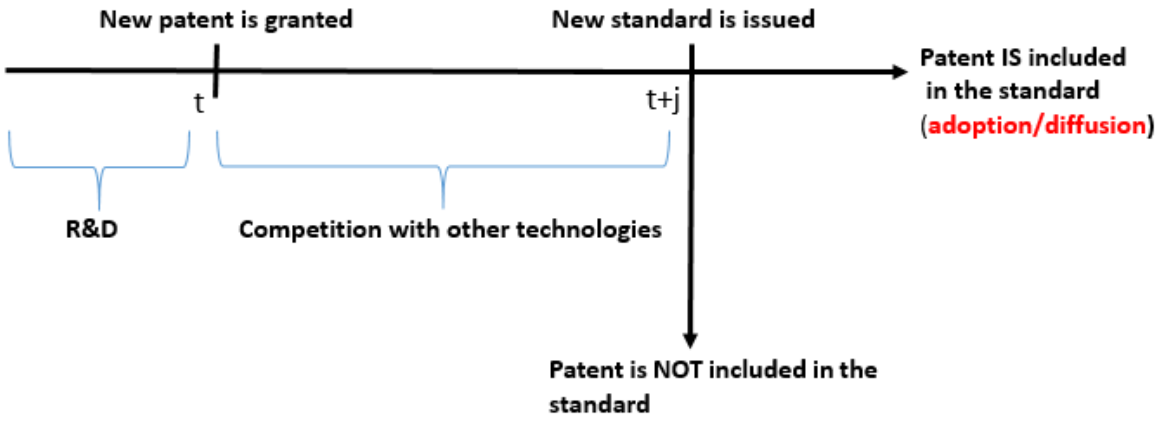
firm (built as value of equity and short/long-term debt at the net of common preferred shares, and expressed in billions of USD), the total market-value of the firm (built as the value of outstanding shares), the net-worth of the firm (i.e. the total value of assets minus liabilities), the age of the firm (expressed in quarters), the q-value of investments (built as the book value of liabilities plus the market value of common equity divided by the book value of assets), leverage (as debt over the book value of assets). As from panel B of Table 1, the proximity measure at the firm-quarter level has a mean equal to 0.34. In our sample, 48% of firms have a positive proximity value. Each firm issues on average 17 patents within a quarter. In the sample, 61% of firms issue at least one patent. Each patent is cited on average 0.7 times in the quarter following the patent grant. The average lag between patent issuance and standard publication (ω) for the sample of firms and patents used is 42 quarters. The average book-value of the firm is 4.32 billion dollars, while the average market-value and net-worth are respectively 11.7 and 2.6 billion dollars. The average age of the firm is 25 years, it has a leverage equal to 20% and a Q-value of investment equal to 1.93.

3 Empirical Analysis

3.1 Set-up

In order to explain clearly our empirical strategy, it is first important to discuss the chain of events that follow innovation activity and that (eventually) lead to the inclu-

Figure 1: FROM PATENT GRANT TO INDUSTRY ADOPTION THROUGH STANDARDIZATION



Notes: This figure sketches the events following the grant of a patent at time t. After j periods following the patent grant, the technology described in the patent is eventually included in a new standard (issued at time $t + j$). If this is the case, the technology described in the patent is adopted at the industry level and diffuses.

sion of a technology in a new standard. For this, consider Figure 1.

Following a period of R&D, a firm can be granted a patent at any point in time t. From this moment onwards, the patent and the underlying new technology will enter in competition with existing patents and technologies from other firms. During this phase, the quality of the patent is always observable to all market participants, including SSOs. Typically, if the new patented technology is considered superior to others and respects specific criteria such as interoperability, compatibility and network effects (Katz and Shapiro, 1985; Farrell and Saloner, 1985) and could lead to industry-wide cost reductions, vertical and horizontal synergies and efficiency gains (Leland, 1979), then SSOs consider it for standardization. Therefore, under the proposal of working groups and after internal votes and the scrutiny of several commissions and technical committees, the new technology is eventually standardized j periods after the initial patent is granted. If this happens, from period $t + j$ the technology now diffuses at the industry level through adoption. In fact, if a firm does not own any patent and technology that align with the new standard, they have incentives to adopt them in order to remain competitive (Schmidt and Steingress, 2022) and being able to market their products in line with the standardized technology. On the other hand, as explained in Bergeaud et al. (2022) firms that already own patents aligned with a newly issued standard benefit from a (temporary) competitive advantage following the standard release as they are able to immediately deploy, scale and market new applications of the standard. Our patent data and semantic analysis allow us to identify i) which firms innovate and which do not; ii) which firms see their technologies being included in a new standard (and to which extent) and which firms do not. By exploiting the heterogeneity in innovation capacity and standardization outcome, we are able to identify the contribution of innovation and technology diffusion (through the process of standardization) to the value of the firm.

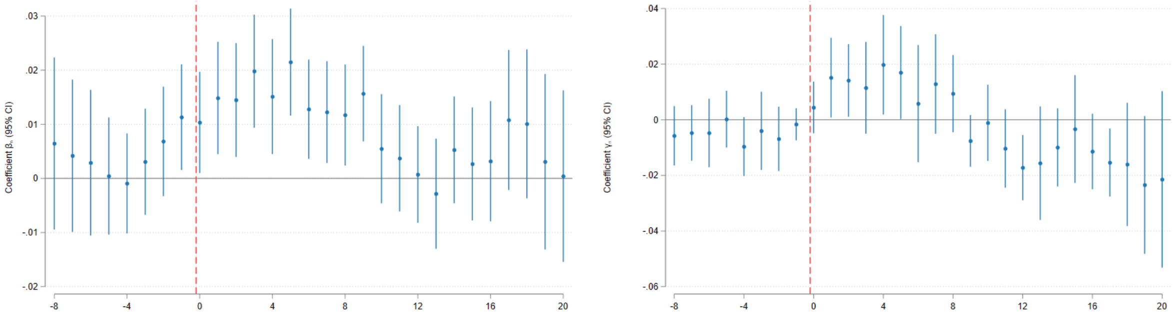
Yet, it is important to stress that several different patents and standards can be released in subsequent periods and that a firm can publish a new patent while contemporaneously older patents are included in a new standard (and viceversa). Therefore, in order to better isolate the effect of the introduction of a new patent and a new standard, we resort to a distributed lead-lag model in which both the innovation and standardization margin are included. The advantage of this approach is twofold. First, as explained also in Hall et al. (2005), a horse-race between the two margins allows to identify the effect of patenting activity netting out the contemporaneous effect of standardization (and viceversa). Second, with respect to a static analysis, the lead-lag component allows to capture the full dynamics of the response following either the release of a new patent or a new standard. In fact, in our setting, we know that a static model or considering the two margins in separate models would lead to a bias since the firm's response to patenting activity (standardization) could be affected also by subsequent and previous patent releases (standards). At the same time, the imputed effect of patenting activity (standardization) would be biased if a standardization event (new patent release) would occur at the same time. In light of this argument, our generic model is described in equation (1):

$$\begin{aligned} \log(Y)_{i,t} = &\sum_{n=-8}^{N=T} \beta_n \log(1 + \mathit{Cit.})_{i,t-n} + \sum_{n=-8}^{N=T} \gamma_n \log(1 + \mathit{Tech.Prox})_{i,t-n} \\ &+ \alpha_i + \phi_{s(i),t} + X'_{i,t-1}\eta + \varepsilon_{i,t} \end{aligned} \tag{1}$$

where $Cit.$ is the quarterly number of forward citations of a new patent (or multiple patents) granted to firm i at time t; $Tech.Prox$ expresses the proximity of the stock of patents of firm i cumulated up to time $t-4$ to the standard publicly released at t, and captures to which extent previous firm-level innovations have been included into the new technology standard. α_i is a firm fixed effect; $\phi_{s(i),t}$ a NAICS 3-digit industry fixed effect interacted with a time fixed effect. This controls for any time effect that might differ across industries (e.g. because of sector-specific demand variation, seasonality, changes in legislation at the industry-level, momentum, etc.). Finally, following Chan et al. (1990), X is a vector of control variables including the age of the firm, the lag of the leverage, q-value of investment. $\varepsilon_{i,t}$ is the error term, which we assume to be normally distributed (conditional on all our covariates) and to be independent across different i.

In this model, β_n (γ_n) measures how the release at $t+n$ of a new patent (standard) influences the dependent variable measured at t, controlling for the effect of all previous and future patent (standard) releases. We will check that the response of the firm to future releases remains insignificant and will present our results by plotting the estimates of β_n and γ_n for all n. As explained in Schmidheiny and Siegloch (2023), under this set-up, identification of β_n and γ_n comes from the different innovation and standardization outcomes over time.

Figure 2: PATENT QUALITY, STANDARDIZATION AND THE BOOK-VALUE OF THE FIRM



(a) Patent quality (b) Proximity to new standard

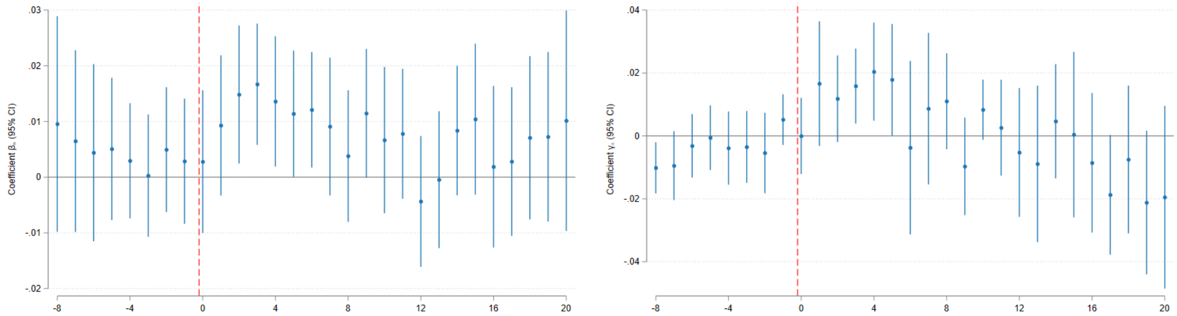
Notes: Figure 2(a) and 2(b) plot the estimated coefficients β_n and γ_n of equation (1) (see Section 3.1). The dependent variable is the log-level of book-value of the firm. In both figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are clustered at the firm-level. The red-dashed line indicates respectively the grant date of a patent and the publication date of the standard.

3.2 Patent quality vs. standardization

Effect on the book-value of the firm. First, we consider the book-value of the firm as dependent variable (i.e. $\log(Y)$). Thus, we estimate model (1) with $T = 20$, i.e. 20 lags, and by clustering errors at the firm level. The figure below plots the estimated β_n and γ_n along with 95% confidence intervals. Consider first the contribution of innovation quality (β_n) to the book-value of the firm. As shown in Figure 2(a), until one quarter before the official patent granting date, no pre-trend is detected: the value of innovating and non-innovating firms is not significantly different. Conversely, the difference between patenting and non-patenting firms starts to be significant from $t-1$ onwards. In particular, the more the patent is cited, i.e. the higher is the perceived patent quality through citations, the bigger is the increase in the firm value (relative to non-patenting firms). This effect is persistent over time and dies out after roughly 2.5 years. This first result corroborates previous evidence in the literature (Hall et al., 2005, Pakes, 1985b, Belenzon and Patacconi, 2013) showing the importance of innovation activity and quality of R&D output for the value of the firm.

When considering the effect of standardization, we obtain similar but less persistent dynamics. As shown in Figure 2(b), in this case no pre-trend is detected in periods before the release of a new standard. When a new standard is published at $t = 0$, firms that align the most with the new standard –i.e. they own technologies now included in the new standard– benefit of an immediate increase in firm value. Such increase is only temporary (roughly one year). This dynamic is coherent with Bergeaud et al. (2022), which show that firms owning technologies included in a new standard benefit of a competitive advantage that translates into a temporary increase in sales and market share.

Figure 3: Patent Quality, Standardization and the Net-worth of the Firm



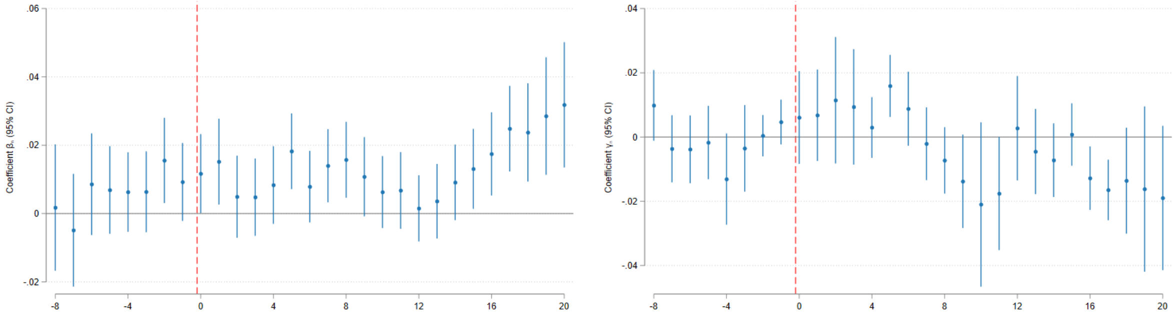
(a) Patent quality (b) Proximity to new standard

Notes: Figure 3(a) and 3(b) plot the estimated coefficients β_n and γ_n of equation (1) (see Section 3.1). The dependent variable is the log-level of net-worth of the firm. In both figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are clustered at the firm-level. The red-dashed line indicates respectively the grant date of a patent and the publication date of the standard.

Effect on the net-worth of the firm. Another important dimension to look at when valuing a company is its net-worth, i.e. the value of the company for the share-holders and investors, which is important to assess the financial health of the firm and future opportunity of growth and financing. In light of this, we use the same model of equation (1) and repeat the analysis above with Y being the net-worth of the company. Consistently with our previous results, Figure 3(a) shows that investors and share-holders see the value of their investment increasing if the firm has published a high-quality patent. This effect is statistically significant two quarters after the grant of the patent and lasts for 5 quarters. Figure 3(b) shows that the net-worth increases when the patents of a company aligns more with the new technology standard. Also in this case, the effect of standardization is less persistent and lasts only two quarters.

Effect on the market-value of the firm. If the previous figures were based on book-values, here we calculate the value of the enterprise by taking into account stock market capitalization (instead of the book value of equity) and use it as dependent variable in model (1). As shown in Figure 4(a), firms that are able to produce and be granted a patent of higher quality see their market-value increasing more. This is particularly true in the long-run. In fact, differently from the results on the book-value of the firm, here there is a clear increase in the firm value —through higher market capitalization– starting only from the third year after the patent grant. On the other hand, short-term effects, in particular the one detected two quarters prior the grant date, can be simply due to the fact that the quality of patents is always observable and markets can anticipate which ones are going to be effectively granted. Therefore they anticipate the effect accordingly. Figure 4(b) shows that firms whose patents are more aligned with the new standard benefit from a larger increase in value five quarters after the introduction of the standard. Also in this case, the effect is not persistent as it lasts only one quarter.

Figure 4: PATENT QUALITY, STANDARDIZATION AND THE MARKET-VALUE OF THE FIRM



(a) Patent quality (b) Proximity to new standard

Notes: Figure 4(a) and 4(b) plot the estimated coefficients β_n and γ_n of equation (1) (see Section 3.1). The dependent variable is the log-level of market-value of the firm. In both figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are clustered at the firm-level. The red-dashed line indicates respectively the grant date of a patent and the publication date of the standard.

In light of this evidence, we conclude that, in a horse-race between innovation quality and standardization, both margins significantly contribute to the book and market-value of the value of the firm and its net-worth. Patenting high quality innovations have a more persistent effect. If the same innovation is also included into a new standard, the process of standardization and diffusion of the underlined technology promises an extra appreciation of the firm. Yet, this further effect is short-lived as the process of diffusion, induced by standardization, allows laggards to catch up and reduces the advantage of industry leaders in the long-run (see Bergeaud et al., 2022).

As discussed in Appendix C, all these results are robust when: i) using another definition of the $\mathtt{Score}$ in the matching between patents and standards; ii) when considering only international standard in the calculation of the score; iii) when controlling for firms' participation in SSOs in the years before the release of a new standard; iv) when grouping firms not by industrial sectors but by clusters defined by competing products as in Hoberg and Phillips (2010) and Hoberg and Phillips (2016). The results are also robust to other definitions of the model, with leads and lags alternatively being 20 or 25. Also, controlling for the interaction between $\log(1 + \mathtt{Cit.})$ and $\log(1 + \mathtt{Tech.Prox})$ does not affect the results.

3.3 The long-run contribution of innovation and standardization

Despite its advantages, model (1) presents also two drawbacks. First, as both independent variables are continuous and expressed in different units of measure, we cannot really compare the different contribution of innovation and standardization to the value of the firm. Second, in the horse-race of innovation vs. standardization, we estimate the dynamic effect of patent granting controlling for the contemporaneous release of a standard (and viceversa). Yet, as sketched in Figure 1, the standardization of a technology (eventually) occurs only after a new patent is granted. In particular, as reported in Panel (B) of Table 1, we know that the technology described in a patent is included in a standard on average 42 quarters after the patent is granted. Therefore, if we want to study how the effect of standardization accumulate on top of innovation, we need to take into account when this effect realizes on average across firms and over time.

In light of this argument, we go around these two drawbacks as follows. First, we estimate model (1) with the dependent variable expressed in change (i.e. $\Delta\log(Y)$ both independent variables substituted by dummies. In particular, we substitute $\log(1+\mathit{Cit.})_{i,t}$ with the dummy $\mathbb{I}(Patent > 0)_{i,t}$ taking value one when firm i is granted a positive number of patents at time t. Similarly, we substitute $\log(1+\mathit{Tech.Prox})_{i,t}$ with $\mathbb{I}(Tech.Prox > 0)_{i,t}$ taking value one when firm i has patents (issued up to $t-4$) describing technologies included in a standard published at time t. Then, we estimate the model with $T = 60$ and collect all estimates of β_n and γ_n, which are now comparable. Finally, we estimate how the effects of innovation and standardization sums up by considering the distribution of lags between the patent grant date and the standard publication date. Thus, we are able to test the linear combination of the probability-weighted and history-dependent effect of standardization on top of the effect of innovation.

In detail, define ω_t as the probability that a patent granted at time t becomes a standard in the same period, i.e. the lag between innovation and standardization is zero. Then, for this group of firms that see immediate conversion of patents into standard, the total effect of releasing a patent at time t is equal to $\beta_t + \omega_t * \gamma_t$, i.e. the increase in value due to innovation activity summed to the (probability weighted) premium if that innovation is included in a standard in the same period. In $t+1$ there is a share of firms ω_{t+1} that see at least one of their patents granted at time t to be included in a standard issued in time $t+1$, i.e. the lag between innovation and standardization is now one period for this group of firms. Then the total effect of releasing a patent at t, cumulated over the first two periods and across the two group of firms, is $\beta_t + \beta_{t+1} + \omega_t * (\gamma_t + \gamma_{t+1}) + \omega_{t+1} * \gamma_t$. In words, on top of the cumulative effect of innovation $(\beta_t + \beta_{t+1})$, we consider the effect standardization for that group of firms that have seen their patents becoming standard already at t $(\omega_t * (\gamma_t + \gamma_{t+1}))$, plus the group of firms that have seen their patents becoming a standard at $t+1$ $(\omega_{t+1} * \gamma_t)$. Similarly, the total effect at time $t+2$ is $\beta_t + \beta_{t+1} + \beta_{t+2} + \omega_t * (\gamma_t + \gamma_{t+1} + \gamma_{t+2}) + \omega_{t+1} * (\gamma_t + \gamma_{t+1}) + \omega_{t+2} * (\gamma_t)$. We proceed recursively to build the cumulative effect of innovation and the joint cumulative effect of innovation and standardization over time up to T periods after the patent grant date. Then, we test all these linear combinations of parameters against the null hypothesis.

Cumulative effect on the book-value of the firm. Figure 5(a) show results when the dependent variable is the book-value of the firm. Relative to firms that do not innovate at all, firms that have been granted a patent at time $t = 0$ see their value increasing up to 1% in the first 38 quarters following the patent grant date. Thereafter, the contribution of innovation start reverting such that the overall increase of firm's value following patent granting is roughly 0.7% over a 60 quarters horizon. Conversely, when considering the cumulative joint effect of innovation and diffusion through standardization, we find that firms whose patents align with a standard experience an increase in value bigger than those that innovate but do not see their patents included into a standard. In particular, firms whose patents are included in a standard –differently from those who do not– see their value increasing up to 1.2%. The divergence between the two effects occur around the 40^{th} quarter following the patent grant. This reflects well the fact that –as discussed in Section 2– the average patent is included into a standard 10 years after patent grant.[5] Both cumulative effects are significantly different from zero.

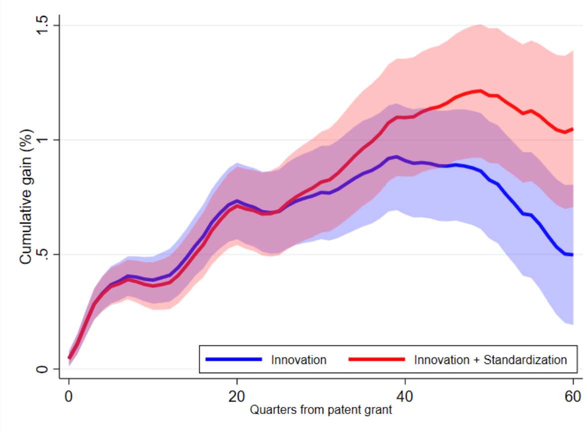
Is it now important to check if the marginal effect of standardization is significant or not. For this, we test the difference between two curves, i.e. we test if the total effect (red line) differs from the innovation effect (blue line). Figure 5(b) show the results. Around the 50^{th} quarter following the patent grant, the increase in value for firms whose technology has been standardized significantly differs from the increase in value for firms that innovate but their technology is not standardized.

Cumulative effect on the net-worth of the firm. When looking at the firm's net-worth we find similar results. As shown in Figure 6(a), after an initial cumulative increase of net-worth of roughly 0.5% (with respect to non-innovating firms), the companies that see their patents being included in a standard maintain that gain beyond the fifth year after the patent grant. Conversely, for firms whose patents do not make it into a standard, their net-worth declines even below the initial level and reaches a cumulative loss of -0.5%. Figure 6(b) shows that the difference between the two effects is significant starting from the 10^{th} year after the patent grant.

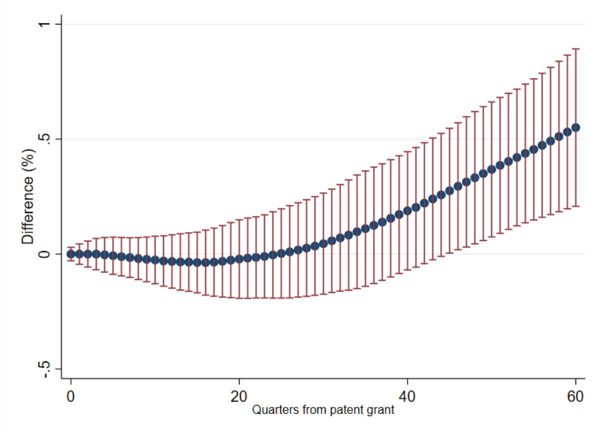
Cumulative effect on the market-value of the firm. When looking at the market-value of the firm, we confirm previous results. As shown in Figure 7(a), with respect to non-patenting firms, companies that see their patents being included into a standard see their market value increasing by 2%. On the other hand, patenting activity grants

[5] Notice also that, for the first 4 quarters following patent grant, the two lines of figure 5(a) perfectly overlaps as –by construction– we consider only patents that were granted at least four quarters prior to the release of the standard. As explained in Bergeaud et al. (2022), this is to reduce as much as possible strategic patenting behavior. In other words, as the content of the new standard leaks, firms might strategically issue patent in the same technological domain just before the publication of the standard.

Figure 5: LONG-RUN CONTRIBUTION OF INNOVATION AND STANDARDIZATION TO THE BOOK-VALUE OF THE FIRM



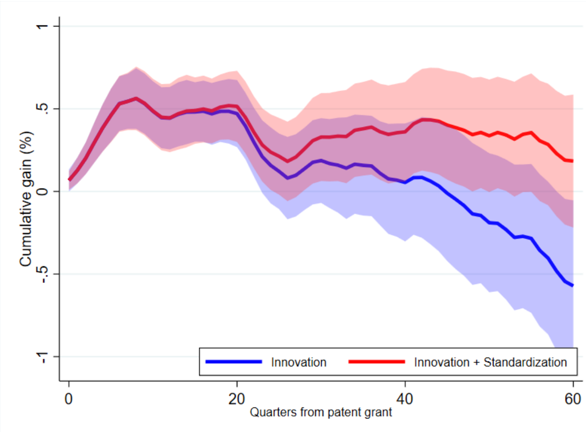
(a) Cumulative Effect



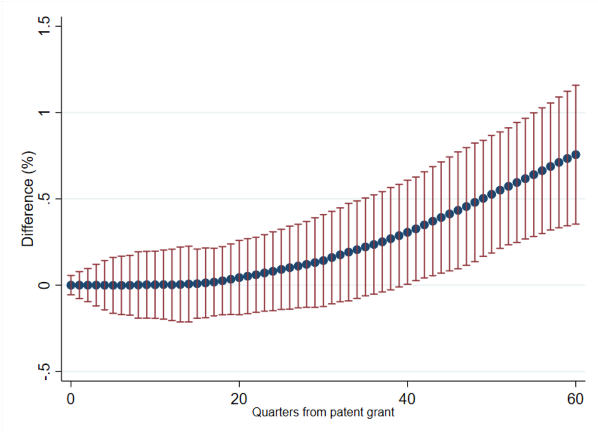
(b) Test of the Difference

Notes: Figure 5(a) and 5(b) plot the cumulative sum of the estimated coefficients β_n and γ_n of equation (1) (see Section 3.1). The dependent variable is the log-level of the-value of the firm. In both figures, the 90% confidence intervals for each point-estimate is reported.

Figure 6: LONG-RUN CONTRIBUTION OF INNOVATION AND STANDARDIZATION TO THE NET-WORTH OF THE FIRM



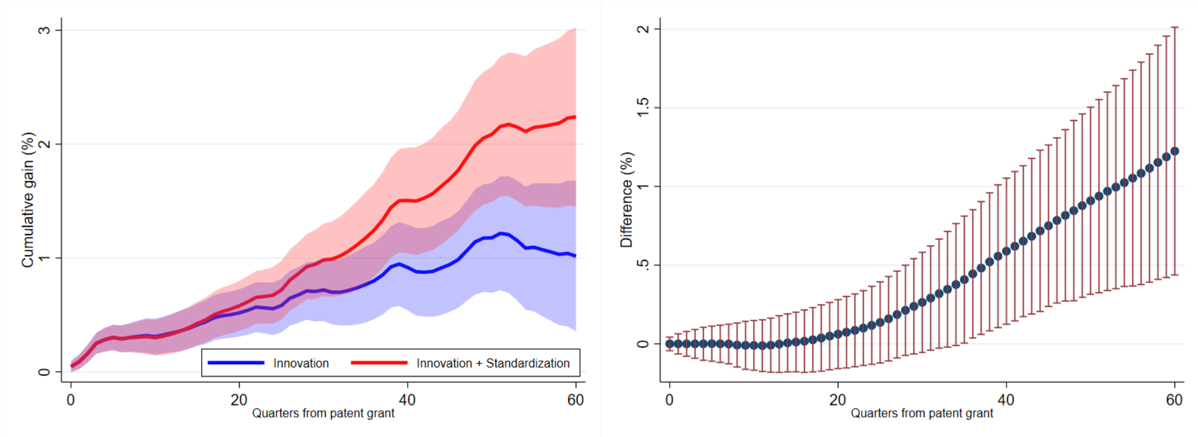
(a) Cumulative Effect



(b) Test of the Difference

Notes: Figure 6(a) and 6(b) plot the cumulative sum of the estimated coefficients β_n and γ_n of equation (1) (see Section 3.1). The dependent variable is the log-level of the-value of the firm. In both figures, the 90% confidence intervals for each point-estimate is reported.

Figure 7: Long-run Contribution of Innovation and Standardization to the Market-value of the Firm



(a) Cumulative Effect

(b) Test of the Difference

Notes: Figure 7(a) and 7(b) plot the cumulative sum of the estimated coefficients β_n and γ_n of equation (1) (see Section 3.1). The dependent variable is the log-level of the-value of the firm. In both figures, the 90% confidence intervals for each point-estimate is reported.

only 1% increase in the market-value of the firm. Figure 7(b) shows that the difference between the cumulative effects of innovation and standardization is statistically significant starting around 9 years after the grant of the patent.

All in all, this results corroborate the idea that innovation is not enough to permanently increase the value of the firm. In fact, if a firm does not see its technology adopted and diffused at industry level (through standardization) the increase in value explained by innovation deteriorates over time. Conversely, firms that see their innovation diffusing through the definition of a standard, increase their value more and maintain it over time. Overall, the contribution of innovation to the total long-run increase in the firm' value is 2/3, whereas the contribution of diffusion through standardization is 1/3.

Yet, innovation intensity and quality of new inventions differ substantially across sectors and firms. Despite the fact that we control for sectoral and firm fixed effect, some industries work on marginal and/or incremental innovation whereas others on breakthrough innovation. For example, the manufacturing sector typically focus on the first type of innovation: firms in this sector tend to innovate on technologies, protocols and practices building on top of previous inventions. On the other hand, the high-tech sector puts efforts in breakthrough inventions that either diffuse or fail without the need of a standard as all firms in this sectors –as their products– are typically innovation intensive. For this reason, in Appendix C.5 we split these results between manufacturing and high-tech companies. As shown in Figure C.14b-C.16b, the results of this section are mostly explained by firms operating in the manufacturing sectors. Conversely, for firms in the tech-sector, the contribution between innovation and diffusion do not significantly differ, but the overall long-run effect is magnified. For example, although the effects of standardization does not significantly increase the long-term book value of the firm following the publication of a standard, the overall effect is 5% (1.6% for manufacturing firm). This suggest that two alternative channels are operating in this case: either standards are extremely effective in immediately leaving the competition field, or standards are not the primary way patents diffuse in the tech-sector, and diffusion occurs very fast.

3.4 Innovation vs. Diffusion: productivity gains vs. rent extraction

All in all, Section 3.2 and 3.3 provides evidence on the effect of innovation and diffusion of novel technologies –through standards definition– on the value of the firm. Now, it is important to understand what exactly technological innovation and diffusion stand for and through which channels the two margins contribute to the value of the firm. There is abundant evidence on the link between innovation activity, R&D expenditure and firm-level productivity (see among the many Watt et al. (2023) and Bartz-Zuccala et al. (2018)). On the other hand, the literature on innovation and competition (see among the many Aghion et al. (2005)) shows that, when a firm take a technological lead, the market become less competitive as the firm temporarily becomes monopolist of the new invention. As long as spillovers and R&D activity do not allow followers to catch up, leaders can extract rents from the market. In light of this, in this section we study which margin –innovation or diffusion– leads to productivity gains or rent extraction.

Productivity gains. Following Watt et al. (2023), we measure firm-level total factor productivity (TFP) by estimating the log-transformation of a simple Cobb-Douglas production function of the form $log(Y) = log(A) + \beta log(K) + (1 - \beta)log(L)$ where Y is output, A is TFP, K is capital and L is labor. In practice, for each firm i in the sample we estimate

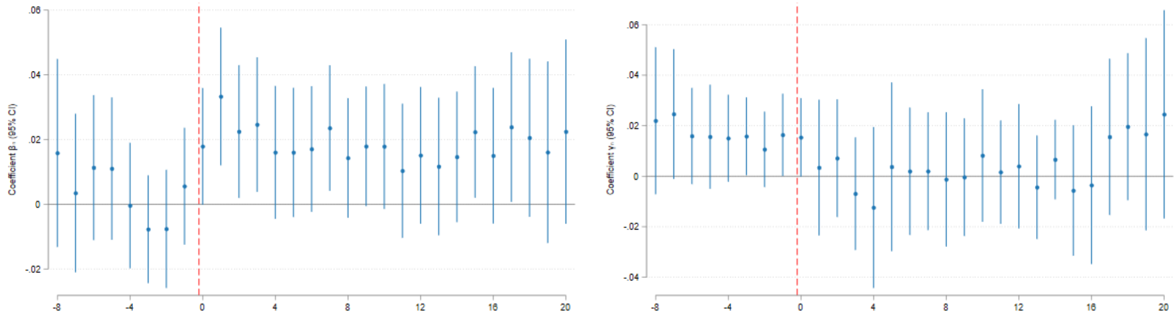
$$log(sales_{i,t}) = \alpha + \beta log(capex_{i,t}) + (1 - \beta)log(emp_{i,t}) + \delta^{qtr} + \varepsilon_{i,t}$$

where clearly $sales_{i,t}$ is sales, $capex_{i,t}$ is capital expenditure and $emp_{i,t}$ is employment.[6] Hence, at the net of the average TFP level α and the seasonal change in TFP captured by the quarterly dummy δ^{qtr}, innovations in TFP are captured by the residual $\varepsilon_{i,t}$. Given this, we use the residual as dependent variable in model (1).

Figure 8(a) shows results for the dynamic effect of the release of a patent on productivity gains: firms releasing patents of higher quality have positive productivity gains.

[6]Notice that Compustat provides employment only at yearly frequency. We linearly interpolate this variable in order to estimate firm-level TFP at quarterly frequency.

Figure 8: PRODUCTIVITY GAINS FROM INNOVATION AND STANDARDIZATION



(a) Patent quality

(b) Proximity to new standard

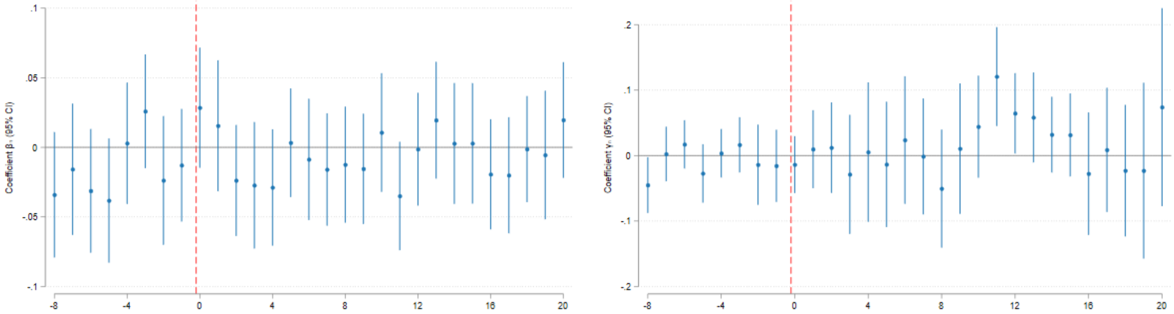
Notes: Figure 8(a) and 8(b) plot the estimated coefficients β_n and γ_n of equation (1) (see Section 3.1). The dependent variable is firm-level productivity gain (see Section 3.4 for details). In both figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are clustered at the firm-level. The red-dashed line indicates respectively the grant date of a patent and the publication date of the standard.

Such gains appears to be very persistent over time. Conversely, Figure 8(b) shows that having a patent, included to some extent into a new standard, does not lead to productivity gains. This result is consistent with the idea that producing a good technology or developing a high quality production procedure/practice increases the productivity of the firm. However, the diffusion of such technology does not provide any further TFP gain for the firm.

In light of this, we now consider how the margin of innovation and diffusion affects the ability of the firm to extract rent from the market. In order to do so we build a simple markup measure $mu_{i,t} = log(sales_{i,t}/cogs_{i,t})$, i.e. the log of sales over costs of goods sold, and we use it as dependent variable in model (1). Despite the large empirical and theoretical debate on how to measure markups, this simple measure should not be biased in the context of our empirical model. In fact, since we are working with logs, the firm specific elasticity of the production function –which shows in more refined measure of firm-level markups like those from De Loecker et al. (2020)– is entirely captured by the firm' fixed effect.

Figure 9 show results. The markup of the firm, i.e. the ability to charge higher prices above the marginal cost, does not change for firms releasing a new and promising technology relative to all others (see figure 9(a)). This suggests that the release of a new promising patent is not sufficient for a firm to distort competition and extract rent from the market. Conversely, when a firm sees its patents being included into a new standard, then such market distortion occurs. In fact, although temporarily, the markup significantly increase for those firms whose patents' features are picked by a standard organization (see figure 9(b)). In fact, as discussed in Bergeaud et al. (2022), firms that happen to have patents closer to a newly released standard benefit from a temporary competitive advantage relative to all others, which translates into a temporary increase in sales and market share. This is because these frontier firms have

Figure 9: RENT EXTRACTION FROM INNOVATION AND STANDARDIZATION



(a) Patent quality

(b) Proximity to new standard

Notes: Figure 9(a) and 9(b) plot the estimated coefficients β_n and γ_n of equation (1) (see Section 3.1). The dependent variable is the markup $mu_{i,t} = log(sales_{i,t}/cogs_{i,t})$. In both figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are clustered at the firm-level. The red-dashed line indicates respectively the grant date of a patent and the publication date of the standard.

already the know-how (patents) to comply with the new standard and start production accordingly. This is not true for firms far away from the technological frontier imposed by the standard, as they have to reorganize and acquire the know-how through further R&D in order to position their selves at the frontier. This mechanism gives a time-window of rent extraction to leading firms.

4 Conclusion

Technological innovation and diffusion play important and different roles for the value of the firm over time. This paper disentangles these two margins and shows how they respectively contributes to the firm' value in the long-run. Yet, to tell one margin from the other is difficult as the process of innovation and diffusion is notoriously endogenous. For this reason, we leverage on a specific and particular process of technology diffusion at the industry level: standardization. In fact, technology standards are defined by national and international organizations to select and promote the widespread use of the best technologies and practices for the production of goods and services. In light of this, we conduct a semantic analysis of standards documents and firms' patents. In particular, we build a measure expressing to which extent the technologies developed by a company are included in a new standard by analysing the text of standards and patents' abstracts. This new measure, along with a measure of patent quality (forward citations) and information on patents and standards' publication dates, allows us to investigate the respective impact of innovation and diffusion (though standardization) on the value of the firm.

As first exercise, we conduct a horse-race analysis between the two margins. Doing so is an empirical challenge as i) firms can release patents in several consecutive periods, while ii) some previously patented technology can be contemporaneously included in a new standard (and viceversa). In light of this, we address this issue through a dispersed lead-lag model that allows to pin down the entire dynamic response of the release of a new patent (standard) while controlling for the release of a new standard (patent) and viceversa. Under this strategy we show that, prior to the patent or standard release, the value of the firm does not differ across firms. In other words, no pre-trend is detected or, at most, there is anticipation of the effect of patenting activity or technology standardization only by one quarter. After the date of patent granting or publication of the standard, the effects differ between the two margins. Patenting activity leads to a persistent increase in the book and market-value and net-worth of the firm. Such increase is larger the higher is the quality of the granted patent and lasts more than a year. Conversely, and consistently with Bergeaud et al. (2022), the effect of standardization is only temporary. In other words, firms whose technology is included in a standard see their value increasing for just few quarters as they have an immediate technological advantage. However, the definition of the standard allow laggard firms to reorganize and catch up in the long-run such that the initial advantage dissipates. Also in this case, the more the patent of a firm overlaps with the specifics described in the standard, the bigger is this temporary increase in value.

As a second exercise, we study the cumulative effect of innovation and diffusion through standardization as the inclusion of patents in a standard is an event posterior to the release of the patent. This allows us to finally quantify the different contribution of the two channels in the long run. To do so, we use the same dispersed lead-lag model but with dummies taking value one in the period when a new a patent is granted and (later) included into a standard. Under this set-up, we find that firms that innovate see an increase in the book-value of the firm by 0.8% in the first 10 years after the release of the patent. At this point, if the patent is included into a standard, the gain in value increase up to 1.2% in the following 5 years otherwise it deteriorates. Similar results are found when looking at the market-value of the firm or at its net-worth.

Finally, we investigate the channels through which the innovation and diffusion margins affect the value of the firm. By studying the evolution of firm-level productivity and markups, we show that the increase in the value of the firm explained by the innovation margin is due to persistent productivity gains that the firm gets from the production of a new promising technology or production practice. On the other hand, the increase in the value explained by the diffusion margin –through the process of standardization– is due to rent extraction. In fact, as explained in Bergeaud et al. (2022), firms that sees their technology being included in a standard have already the know-how to comply with it and start production accordingly. This is not true for firms far away from the technological frontier imposed by the standard, as they have to reorganize and acquire knowledge through further R&D in order to position their selves at the frontier. This mechanism gives a time-window of rent extraction to leading firms.

To sum up, this paper shows that innovation is not enough for the firm to increase or at least maintain its value in the long-run. For this, the diffusion of its technologies is fundamental. Under our empirical analysis, we find that that technology diffusion –through the inclusion of patents into standards– explains 40% of the long-run increase in the book-vale of the firm; 50% of the increase in the market-value of the firm and its net-worth. Such increase in value builds up over time through two different channels. The increase in value explained by innovation activity is due to productivity gains. The increase in value due to diffusion is explained by rent-extraction of firms who see their patent being standardized.

References

Abbas, Assad, Limin Zhang, and Samee U. Khan, "A literature review on the state-of-the-art in patent analysis," *World Patent Information*, 2014, *37*, 3–13.

Adams, Stephen, "The text, the full text and nothing but the text: Part 1–Standards for creating textual information in patent documents and general search implications," *World Patent Information*, 2010, *32* (1), 22–29.

Aghion, Philippe and Peter Howitt, "A Model of Growth through Creative Destruction," *Econometrica*, March 1992, *60* (2), 323–351.

_ , Nicholas Bloom, Richard Blundell, Rachel Griffith, and Peter Howitt, "Competition and Innovation: an Inverted-U Relationship," *The Quarterly Journal of Economics*, 2005, *120* (2), 701–728.

Argente, David, Salomé Baslandze, Douglas Hanley, and Sara Moreira, "Patents to products: Product innovation and firm dynamics," FRB Atlanta Working Paper 2020-4, Federal Reserve Bank of Atlanta 2020.

Arts, Sam, Bruno Cassiman, and Juan Carlos Gomez, "Text matching to measure patent similarity," *Strategic Management Journal*, 2018, *39* (1), 62–84.

Austin, David H, "An event-study approach to measuring innovative output: The case of biotechnology," *The American economic review*, 1993, *83* (2), 253–258.

Baron, Justus and Daniel F. Spulber, "Technology Standards and Standard Setting Organizations: Introduction to the Searle Center Database," *Journal of Economics & Management Strategy*, 2018, *27* (3), 462–503.

Bartz-Zuccala, Wiebke, Pierre Mohnen, and Helena Schweiger, "The role of innovation and management practices in determining firm productivity," *Comparative Economic Studies*, 2018, *60* (4), 502–530.

Basu, Susanto and John G. Fernald, "Information and Communications Technology as a General Purpose Technology: Evidence from U.S. Industry Data," *Federal Reserve Bank of San Francisco Economic Review*, 2008, pp. 1–15.

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

Bergeaud, Antonin and Cyril Verluise, "The rise of China's technological power: the perspective from frontier technologies," Discussion Paper 1876, Centre for Economic Performance 2022.

_ , Julia Schmidt, and Riccardo Zago, "Patents that Match your Standards: Firm-level Evidence on Competition, Innovation and Growth," *CEPR Working Paper*, 2022.

_ , Yoann Potiron, and Juste Raimbault, "Classifying patents based on their semantic content," *PloS one*, 2017, *12* (4), e0176310.

Bloom, Nicholas, Tarek Alexander Hassan, Aakash Kalyani, Josh Lerner, and Ahmed Tahoun, "The Diffusion of Disruptive Technologies," Working Paper 28999, National Bureau of Economic Research July 2021.

Chan, Su Han, John D Martin, and John W Kensinger, "Corporate research and development expenditures and share value," *Journal of Financial Economics*, 1990, *26* (2), 255–276.

Chavalarias, David and Jean-Philippe Cointet, "Phylomemetic patterns in science evolution—the rise and fall of scientific fields," *Plos One*, 2013, *8* (2), e54847.

Dechezleprêtre, Antoine, David Hémous, Morten Olsen, and Carlo Zanella, "Induced automation: evidence from firm-level patent data," Technical Report 384, University of Zurich, Department of Economics 2021.

Eberhart, Allan C, William F Maxwell, and Akhtar R Siddique, "An examination of long-term abnormal stock returns and operating performance following R&D increases," *The Journal of Finance*, 2004, *59* (2), 623–650.

Farrell, Joseph and Garth Saloner, "Standardization, Compatibility, and Innovation," *RAND Journal of Economics*, Spring 1985, *16* (1), 70–83.

Geroski, Paul A, "Models of technology diffusion," *Research policy*, 2000, *29* (4-5), 603–625.

Grossman, Gene M. and Elhanan Helpman, "Quality Ladders in the Theory of Growth," *The Review of Economic Studies*, 1991, *58* (1), 43.

Hall, Bronwyn H., Adam Jaffe, and Manuel Trajtenberg, "Market Value and Patent Citations," *RAND Journal of Economics*, Spring 2005, *36* (1), 16–38.

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

_ **and** _ , "Text-based network industries and endogenous product differentiation," *Journal of Political Economy*, 2016, *124* (5), 1423–1465.

Jovanovic, Boyan and Peter L. Rousseau, "General Purpose Technologies," in Philippe Aghion and Steven Durlauf, eds., *Handbook of Economic Growth*, Vol. 1, Elsevier, 2005, pp. 1181–1224.

Kang, Byeongwoo and Rudi Bekkers, "Just-in-time patents and the development of standards," *Research Policy*, 2015, *44* (10), 1948–1961.

Katz, Michael L. and Carl Shapiro, "Network Externalities, Competition, and Compatibility," *American Economic Review*, June 1985, *75* (3), 424–440.

Kelly, Bryan, Dimitris Papanikolaou, Amit Seru, and Matt Taddy, "Measuring Technological Innovation over the Long Run," *American Economic Review: Insights*, September 2021, *3* (3), 303–20.

Kindleberger, Charles P., "Standards as Public, Collective and Private Goods," *Kyklos*, 1983, *36* (3), 377–396.

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman, "Technological Innovation, Resource Allocation, and Growth," *The Quarterly Journal of Economics*, 2017, *132* (2), 665–712.

Kuhn, Jeffrey, Kenneth Younge, and Alan Marco, "Patent citations reexamined," *The RAND Journal of Economics*, 2020, *51* (1), 109–132.

Leland, Hayne E, "Quacks, lemons, and licensing: A theory of minimum quality standards," *Journal of Political Economy*, 1979, *87* (6), 1328–1346.

Loecker, Jan De, Jan Eeckhout, and Gabriel Unger, "The rise of market power and the macroeconomic implications," *The Quarterly Journal of Economics*, 2020, *135* (2), 561–644.

Nicholas, Tom, "Does innovation cause stock market runups? Evidence from the great crash," *American Economic Review*, 2008, *98* (4), 1370–96.

Pakes, Ariel, "On patents, R & D, and the stock market rate of return," *Journal of political economy*, 1985, *93* (2), 390–409.

_ , "On Patents, R & D, and the Stock Market Rate of Return," *Journal of Political Economy*, 1985, *93* (2), 390–409.

Romer, Paul M, "Endogenous Technological Change," *Journal of Political Economy*, October 1990, *98* (5), 71–102.

Rysman, Marc and Timothy Simcoe, "Patents and the Performance of Voluntary Standard-Setting Organizations," *Management Science*, November 2008, *54* (11), 1920–1934.

Schmidheiny, Kurt and Sebastian Siegloch, "On event studies and distributed-lags in two-way fixed effects models: Identification, equivalence, and generalization," *Journal of Applied Econometrics*, 2023, *38* (5), 695–713.

Schmidt, Julia and Walter Steingress, "No double standards: Quantifying the impact of standard harmonization on trade," *Journal of International Economics*, 2022, *137*, 103619.

Szewczyk, Samuel H, George P Tsetsekos, and Zaher Zantout, "The valuation of corporate R&D expenditures: Evidence from investment opportunities and free cash flow," *Financial Management*, 1996, pp. 105–110.

Watt, Abigail, James McCann, and Jeremy Lawson, *Innovation, Productivity and Firm Performance*, Centre for Economic Policy Research, 2023.

Webb, Michael, Nick Short, Nicholas Bloom, and Josh Lerner, "Some facts of high-tech patenting," Working Paper w24793, National Bureau of Economic Research 2018.

FOR ONLINE PUBLICATION: APPENDIX

A Data

A.1 Standards data

Variables used. We rely on the following information from a `Perinorm` dataset, which is part of the Searle Centre Database on Technology Standards and Standard Setting Organizations (see Baron and Spulber, 2018). In particular, we use the following information:

- *Identifier*: Each standard document is registered with a unique identifier from `Perinorm`.
- *Publication date*: The date of the release (publication) of the standard by the respective SSO.
- *Equivalences*: A standard can be released by several SSOs. Indeed, the internationalization of the standard-setting process where the bulk of standards originates in supranational SSOs such as European SSOs (ETSI, CEN, CENELEC) or international SSOs (ISO, ITU, IEC) results in the co-existence of equivalent standards in `Perinorm`. A standard developed by an international SSO is often accredited by national SSOs to include it in the national standard catalogue. Similarly, accreditations by several SSOs in the same country can be observed, often due to the standard being developed jointly by two or more SSOs. Two standards can be considered equivalent if their content are the same, but they often differ with respect to the release date and the language used in the standard document.
- *Version history*: Standards are constantly updated and several versions can succeed or supersede a previous version. In the latter case, a subsequent standard explicitly replaces a former version whereas the former case implies just a simple update. SSO-specific norms determine the details. Given some of the technical complexities, it is also possible that several standards share a common previous version because standard projects are split into different directions.
- *ICS classification*: The International Classification of Standards is a classification system maintained by the International Organization for Standardization, aimed at covering all possible technical or economic sectors that standards are govering. The ICS classes are composed of three levels, the first one (two digits) designating a general field such as 49 – Aircraft and space vehicle engineering, followed by a second level (three digits) such as 49.030 – Fasteners for aerospace construction, and sometimes a third level (two digits) such as 49.030.10 – Screw threads.
- *Keywords*: `Perinorm` is a bibliographical database, which allows subscribers to search for a standard and to purchase the standard document. To facilitate the search, keywords have been assigned to each standard document. These comprise both 1-grams such as "automation" or 3-grams such as "internal combustion engine".

Cleaning. We clean the standards data, in particular with respect to the publication dates, the equivalences, the version history, ICS classification as well as the keywords.

For some publication dates, the month or the day of the date are missing in which case we assume December for the month and 28 for the day, thus implicitly favoring standards for which the date information is complete.

For some of the equivalences, there is additional information on whether a standard is identical/equivalent or not equivalent. As we want to regroup only those standards that are identical, we correct the list of equivalences and exclude non-equivalent standards. Du to misreporting or chronological reporting, a single standard observation does not necessarily reveal all equivalences. In the case of chronological reporting, only equivalences known at the time of the release are listed and subsequent equivalences are only reported for newly released standards. The identification of equivalent standards is implemented with the algorithm described below.

We take the list of standard identifiers that constitute the version history of each standard document and identify prior versions by comparing the publication dates of these identifiers with the standard document in question. If there is at least one standard with prior publication date in the version history, the standard is not considered a first version.

ICS classifications can be erroneous and are cleaned to only include official codes, respecting the format designed by the ICS.

Keywords are cleaned and processed as described in Appendix B below.

Identifying equivalences. We use graph theory to identify all standards that belong to one group by assigning them the same group identifier. In particular, we use the following breadth-first search algorithm (which we specifically adapt to the structure of the dataset) to connect all standards by exploring their equivalences:

1. Initialize the group identifier, equal to a standard's row number in the dataset, for each standard.
2. Starting with $n = 1$, store the group identifier of standard n in the database (i.e. A).
3. Add the group identifiers of the equivalent standards, i.e. B, to the vector of stored group identifiers.
4. Note the smallest element of the vector of stored group identifiers.
5. Modify the group identifiers of standard n and its equivalent standards by assigning them the value identified in step 4 (i.e. A and B will have the same group identifier).
6. Delete the stored group identifiers.
7. Go on to the next standard $n + 1$ and repeat from step 2 onwards.

In order to minimize the computing power needed to run the algorithm, we use a simple hash function to build a dictionary of all standards whose IDs, which are strings, are mapped one-to-one to numeric values.

Relevant subset and grouping of keywords. For each group of standards (defined as regrouping all equivalent standard documents), we exclude within-country duplicate standard releases, only keeping the earliest standard release. We then restrict the sample to first versions only. All ICS and keywords are aggregated on the level of the group identifier. Only unique keywords are kept to avoid double counting due to the fact that a group includes a large number of individual, equivalent standard documents.

B Matching

B.1 Matching procedure

B.1.1 Brief outline of the matching procedure

Our goal is to find the patents that are the "closest" to a given standard. Our approach relies on the set of keywords associated with a standard, which we take to be a sufficient information set to describe the standard, and on the abstract of patents. More specifically, for each standard, we scan our patent database and give a score for each patent that reflects how relevant these standard's keywords are to describe the patent's abstract. One of the main challenge with this type of large scale data mining approach is to design a method that is suitable for big data (there are around 0.8m standards and 1.9m patents in our dataset). We briefly present our approach below.

The standard database includes, among others, a standard identifier, the title, a release date and a number of keywords that were manually provided by `Perinorm` staff when incorporating a standard into the database. For example, the Austrian standard AT98957039 with the title "OENORM Aerospace series - Nickel base alloy NI-B15701 (NiPd34Au30) - Filler metal for brazing - Wire" is included in the database with the following keyword information:

```
standard id   date         ICS          keywords
AT98957039    01/07/1997   49.025.15    Aerospace transport*Air
                                        transport*Brazing
                                        alloys*Nickel base
                                        alloys*Space transport*Wires
```

We process these keywords as follows.

1. **Stemming and cleaning keywords**: this first step consists in "normalizing" the set of keywords contained in each standard by removing upper-case letter, punctuation and "stop-words" (*the*, *at*, *from* etc...). We then keep only the stem of each word.[7]

2. **Constructing k-grams**: the second step consists in associating successive stems into one unique semantic unit. These "multi-stems", or *k-grams* are constructed

[7]Families of words are generally derived from a unique root called stem (for example *compute*, *computer*, *computation* all share the same stem *comput*).

as groups of size k, with $k \leqslant 3$. The rationale from considering group of words can be illustrated with the example of a standard containing "air conditionning" as one of its keywords. If we do not consider k-grams in addition to single stems, then we would be screening the patent database for the stems *air* and *condition*, which are clearly irrelevant in that case. Thus, at the end of this procedure, we can associate for each standard j a set $\mathcal{A}(j)$ of 1-grams, 2-grams and 3-grams taken from its keywords.[8]

3. **Computing Inverse Document Frequency**: we then associate for each k-grams $l \in \bigcup_{j \in \mathcal{J}} \mathcal{A}(j)$ a quantity that seeks to measure how frequent this k-gram is. This is known as the inverse document frequency and is defined as follow:

$$\mathrm{IDF}(l) \equiv \log \left(\frac{1 + |\mathcal{J}|}{1 + \sum_{j \in \mathcal{J}} \mathbb{1}(l \in \mathcal{A}(j))} \right)$$

   Where $\mathbb{1}(X)$ is equal to 1 if X is true and $|\mathcal{J}|$ is the cardinal of $\mathcal{J}$ (the number of standards). In other words, $\mathrm{IDF}(l)$ is calculated from the inverse of the share of standards that contains k-gram l.

4. **Removing uninformative k-grams**: from the set of k-grams l and their associated IDF, we further restrict the sample by removing k-grams whose IDF is below a given threshold T. The choice of such a threshold will be discussed below and results from a trade-off between efficiency and exhaustiveness (see Chavalarias and Cointet, 2013 and Bergeaud et al., 2017 for a discussion).

Whereas we have keywords already provided in the standards database, this is not the case for the patents where we rely on their abstracts to extract keywords as described further below. The EPO patent EP0717749A4 with the title "Self-addressable self-assembling microelectronic systems and devices for molecular biological analysis and diagnostics" is included in the database with the following information:

patent id	date	IPC	abstract
49188362	25/01/2000	G01/C40	A self-addressable, self-assembling microelectronic device is designed and fabricated to actively carry out and control multi-step and multiplex molecular biological reactions ...

We use these abstracts to form k-grams contained in the abstract of patents by considering all possible combinations of words in these continuous up to k-grams of 3 words.

[8]One might wonder why we do not consider groups of words as they appear in the standards' keywords list. The reason is that we believe that matching part of a k-gram still brings some information. Consider the (real) case of a keyword "ISO screw thread", then a patent containing the 2-gram "screw thread" is still highly relevant.

We proceed to the same cleaning and stemming procedure as for standards' keywords. Note that contrary to other studies that have used semantic analysis on patents' abstract (see e.g. Bergeaud et al., 2017 or more generally regarding patents Adams, 2010), we are not doing anything to select words based on their grammatical functions in the abstract. This is because the number of standards' keywords is limited and there is no need to reduce the size of the patents' abstracts to improve the performance of the algorithm.

B.1.2 Measuring proximity

Once the procedure detailed above is done, we are left with a set of patent $i \in \mathcal{P}$ and a set of standards $j \in \mathcal{J}$. For each patent i, we denotes the set of extracted k-grams by $\mathcal{B}(i)$ while for each standards j, we denotes the set of k-grams by $\mathcal{J}(j)$. We want to compute a score $S(i, j)$ for each pair of a patent and a standard based on the semantic proximity between $\mathcal{B}(i)$ and $\mathcal{A}(j)$. In constructing this score, we keep several criteria in mind:

- We want to give more weight to keywords that have a high IDF since they are more likely to be useful in describing the specificity of a given standard.
- We want to favor a patent whose abstract matches different keywords rather than a patent that matches the same keyword several times.[9]. We therefore only consider keywords once even if they show up several times in a patent abstract.
- We want to value the length of the matched k-grams (i.e. a matching 3-gram will have more relevance than a matching 1-gram).

One natural way to do this would be to consider the following score:

$$S_1(i, j) = \sum_{l \in \mathcal{A}(j)} \frac{n(k, i)}{|\mathcal{B}(i)|} \mathrm{IDF}(l) \tag{B.1}$$

where we have denoted

$$n(l, i) \equiv \sum_{k \in \mathcal{B}(i)} \mathbb{1}(l = k) \tag{B.2}$$

the number of times k-gram l appears in $\mathcal{B}(i)$. This score simply counts the number of times a k-gram in $\mathcal{A}(j)$ appears in patent i's abstract, weighted by the inverse document frequency of this k-gram and standardized by the length of patent i's abstract $|\mathcal{B}(i)|$. However, such a score does not fully take into account the length of the different k-grams, the number of common k-grams between $\mathcal{A}(j)$ and $\mathcal{B}(i)$. We therefore introduce

[9]Indeed, a patent abstract $\mathcal{B}(i)$ can contain the same k-gram several times.

a more complete structure:

$$S_2(i,j) = \sum_{l \in \mathcal{A}(j)} \sqrt{\left(\frac{n(k,i)}{|\mathcal{B}(i)|}\right)^{s(l)}} \mathrm{IDF}(l) \left(|\mathcal{A}(j) \cap \mathcal{B}(i)|\right) \tag{B.3}$$

which compared to S_1: (1) adds a multiplicative term for the number of common k-grams between $\mathcal{A}(j)$ and $\mathcal{B}(i)$; (2) adds a power terms $s(l)$, which returns the length of the k-gram l ($s(l) = 1, 2$ or 3) to the number of concurrences between $\mathcal{A}(j)$ and $\mathcal{B}(i)$ so as to give more weights to longer k-grams and (3) adds a concave function to reduce the impact of the term frequency in the patent to increase the impact of the number of distinct common keywords. In the paper, we consider S_2 as our main measure but we also report results using S_1 in Appendix C.1, as robustness.

B.1.3 Implementation in practice

The size of the databases poses technical difficulties. Because there are more than 21 million priority patents and over 640,000 unique standard documents, we are faced with over 1.4×10^{13} possible matches. We proceed as follows. We first extract all the cleaned and stemmed k-grams from the standards keywords and store these as a dictionary with which all patent abstracts are compared in the next step. When extracting k-grams from the patent abstract, we do not store any k-grams that do not appear in our dictionary of admissible keywords obtained from the standards keywords. We do so for two reasons. First, as the goal of the keyword extraction from patent abstracts is to match those to standard keywords, we do not need to store redundant keywords as they do not match with anything that is in our standards database. Second, the keyword extraction proceeds in forming k-grams from a continuous text that has been stemmed, thus building a large number of k-grams void of sense. For example, from the sentence "The authentication procedure allows for personal data protection." which becomes "authenticat proced allow personal data protect" after stemming, the following 3-grams are extracted from the text: "authenticat proced allow", "proced allow personal", "allow personal data", "personal data protect" as well as the corresponding 2-grams. Only the 3-gram "personal data protect" as well as the 2-grams "authenticat proced", "personal data" and "data protect" are probably meaningful, which is why the use of a pre-defined dictionary as a benchmark is warranted.

After extracting all keywords for each standard, we regroup all associated standard identifiers. We store for each unique keyword in the standards database its associated IDF and a list of all standard ids that correspond to this keyword. We do so similarly for the patent database and store additionally for each associated patent id the number of occurrences of the keyword in the patent abstract as well as the total number of keywords per patent id. Equipped with these two lists, we can match patents to standards by simply building the Carthesian product of the associated standard identifiers and the associated patent identifiers of each keyword. We then add up all patent-standard combinations across all common keywords to compute the scores as described above.

B.2 Matching of ICS and IPC classes

One way to evaluate the quality of our matching procedure is to verify how individual patent-standard matches relate broad categories of the IPC (patents) and ICS (standards) classifications. Essentially, we are linking the two classification systems on the basis of the individual matches obtained in our matching procedure. For the IPC classification, we consider the second hierarchical level, which is the IPC class, and for which 122 classes exist (for example C06 – Explosives; matches.). For the ICS classification, we consider the two-digit level which comprises 40 different ICS fields (for example 49 – Aircraft and space vehicle engineering). Summing the score over all patent-standard combinations that belong to the same IPC-ICS combinations; we obtain a concordance between the two classification systems. Table B.1 lists the closest IPC class for every ICS field.

Table B.1: ICS-IPC CONCORDANCE

ICS	ICS description	IPC	IPC description
1	Generalities. Terminology. Standardization. Documentation	E04	Building
3	Services. Company Organization, Management And Quality. Administration. Transport. Sociology	G06	Computing; calculating; counting
7	Mathematics. Natural Sciences	C12	Biochemistry; beer; spirits; wine; vinegar; microbiology; enzymology; mutation or genetic engineering
11	Health Care Technology	A61	Medical or veterinary science; hygiene
13	Environment. Health Protection. Safety	C02	Treatment of water, waste water, sewage, or sludge
17	Metrology And Measurement. Physical Phenomena	G01	Measuring; testing
19	Testing	G01	Measuring; testing
21	Mechanical Systems And Components For General Use	F16	Engineering elements or units; general measures for producing and maintaining effective functioning of machines or installations; thermal insulation in general
23	Fluid Systems And Components For General Use	F16	Engineering elements or units; general measures for producing and maintaining effective functioning of machines or installations; thermal insulation in general
25	Manufacturing Engineering	B23	Machine tools; metal-working not otherwise provided for
27	Energy And Heat Transfer Engineering	G21	Nuclear physics; nuclear engineering
29	Electrical Engineering	H01	Basic electric elements
31	Electronics	H01	Basic electric elements
33	Telecommunications. Audio And Video Engineering	H04	Electric communication technique
35	Information Technology. Office Machines	H04	Electric communication technique

Continuation of Table B.1

ICS	ICS description	IPC	IPC description
37	Image Technology	G03	Photography; cinematography; analogous techniques using waves other than optical waves; electrography; holography
39	Precision Mechanics. Jewellery	A44	Haberdashery; jewellery
43	Road Vehicles Engineering	B60	Vehicles in general
45	Railway Engineering	B64	Aircraft; aviation; cosmonautics
47	Shipbuilding And Marine Structures	B63	Ships or other waterborne vessels; related equipment
49	Aircraft And Space Vehicle Engineering	B64	Aircraft; aviation; cosmonautics
53	Materials Handling Equipment	B66	Hoisting; lifting; hauling
55	Packaging And Distribution Of Goods	B65	Conveying; packing; storing; handling thin or filamentary material
59	Textile And Leather Technology	D01	Natural or artificial threads or fibres; spinning
61	Clothing Industry	A44	Haberdashery; jewellery
65	Agriculture	A01	Agriculture; forestry; animal husbandry; hunting; trapping; fishing
67	Food Technology	A23	Foods or foodstuffs; their treatment, not covered by other classes
71	Chemical Technology	F42	Ammunition; blasting
73	Mining And Minerals	E21	Earth or rock drilling; mining
75	Petroleum And Related Technologies	C07	Organic chemistry
77	Metallurgy	C23	Coating metallic material; coating material with metallic material; chemical surface treatment; diffusion treatment of metallic material; coating by vacuum evaporation, by sputtering, by ion implantation or by chemical vapour deposition, in general; inhib
79	Wood Technology	B27	Working or preserving wood or similar material; nailing or stapling machines in general
81	Glass And Ceramics Industries	C03	Glass; mineral or slag wool
83	Rubber And Plastic Industries	C08	Organic macromolecular compounds; their preparation or chemical working-up; compositions based thereon
85	Paper Technology	D21	Paper-making; production of cellulose
87	Paint And Colour Industries	B05	Spraying or atomising in general; applying liquids or other fluent materials to surfaces, in general
91	Construction Materials And Building	E04	Building
93	Civil Engineering	E02	Hydraulic engineering; foundations; soil-shifting
95	Military Engineering	F41	Weapons
97	Domestic And Commercial Equipment. Entertainment. Sports	A63	Sports; games; amusements

C Robustness checks

C.1 Main results with a different definition of technological proximity

We want to check whether our results differ if we use another methodology to compute scores in the process of matching patents to standards. As explained in Appendix B.1.2, there are multiple features that we want to consider in constructing the score at the patent-standard level that all capture the idea of semantic proximity. Here, we re-estimate the results of Section 3.2 when using a different definition of the score to build the firm-level measure of technological proximity. In particular, we use the definition of $S_1(i,j)$ in equation (B.1) of Appendix B.1.2 as an alternative which consists in dropping the power term $s(l)/2$ (the term $s(l)$ corresponds to the length of the k-gram l). As Figure C.1(a)-C.3(b) show, results do not change substantially. Using other scores yields similar results, they are available upon request to the authors.

C.2 Main results controlling for SSO membership

We use data from Baron and Spulber (2018) on SSO membership such that we are able to identify those firms that are active in working groups and technical committees of a SSO. The data also include information on the year of the firm's membership. The data start in 1996, and we match it to our firm-level dataset. We find that 29% of the firms in our sample are a member of a SSO at some point between 1996 and 2010. Then, we build a dummy variable $\mu_{i,t}$ equal to one if the firm i is a member of a SSO during the current and two previous years. We then augment our baseline model as follows:

$$\begin{aligned}\log(Y)_{i,t} = &\sum_{n=-8}^{N=T} \beta_n \log(1 + \mathit{Cit.})_{i,t-n} + \sum_{n=-8}^{N=T} \gamma_n \log(1 + \mathit{Tech.Prox})_{i,t-n} \\ &+ \sum_{n=-8}^{N=T} \xi_n \mu_{i,t+n} + \alpha_i + \phi_{s(i),t} + X'_{i,t-1}\eta + \varepsilon_{i,t}. \end{aligned} \tag{C.1}$$

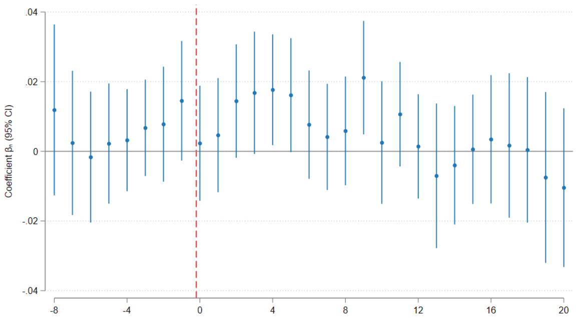
This model allows us to check whether the effect of standardization (captured by the γ_n-coefficients) remains significant. As Figure C.4(a)-C.6(b) show, this is indeed the case.[10]

C.3 Main results excluding standards from American SSOs

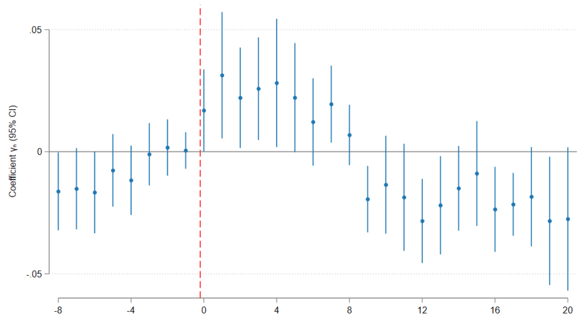
Among all standards in our database, 15% of them are issued by American SSOs. We believe that US firms may have bigger influence on these SSOs rather than on international ones. For this reason, we exclude these American standards from the computation of the score. Then, we build a new variable $\mathrm{Tech.Prox}$ that excludes the scores

[10] Results do not qualitatively change when defining the dummy $\mu_{i,t}$ equal to one only in the year of membership, or when considering a time-invariant dummy taking value one if a firm has been a member at some point.

Figure C.1: Results for the Book-value of the Firm with another proximity measure

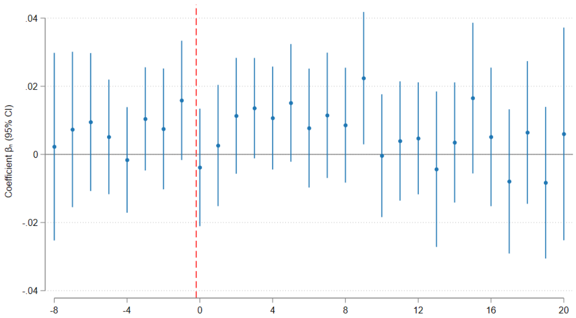


(a) Patent quality

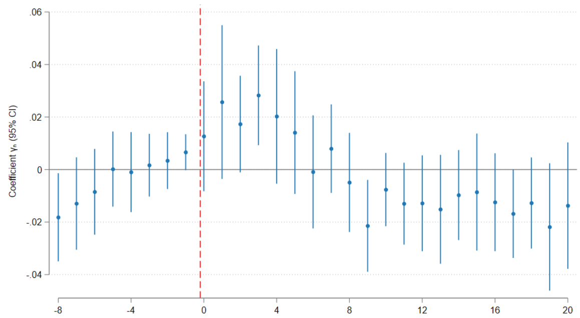


(b) Proximity to new standard

Figure C.2: Results for the Net-worth of the Firm with another proximity measure

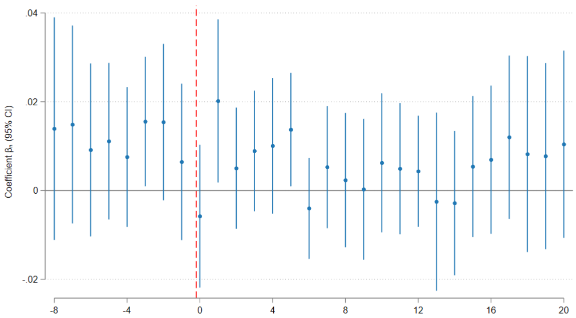


(a) Patent quality

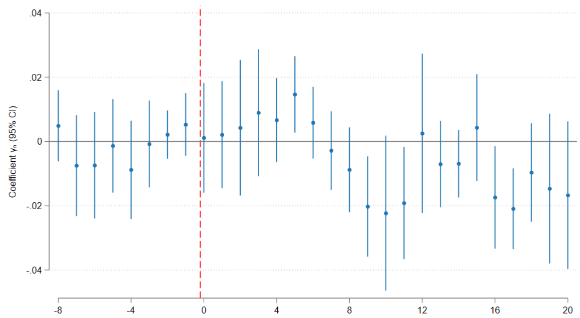


(b) Proximity to new standard

Figure C.3: Results for the Market-value of the Firm with another proximity measure

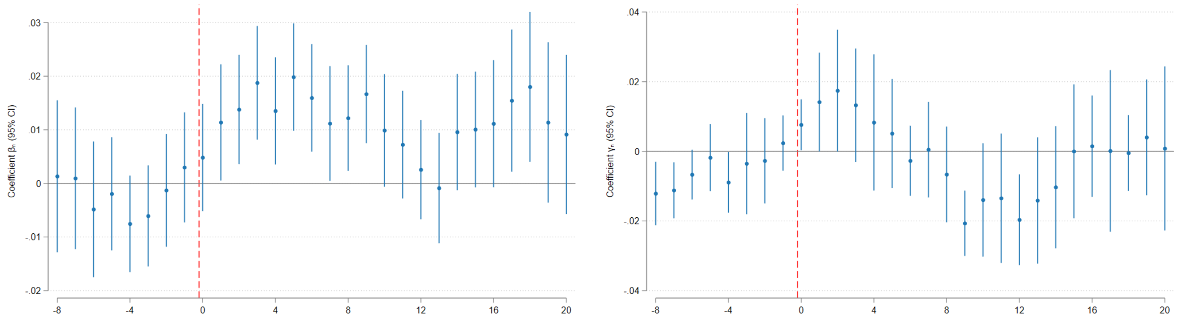


(a) Patent quality



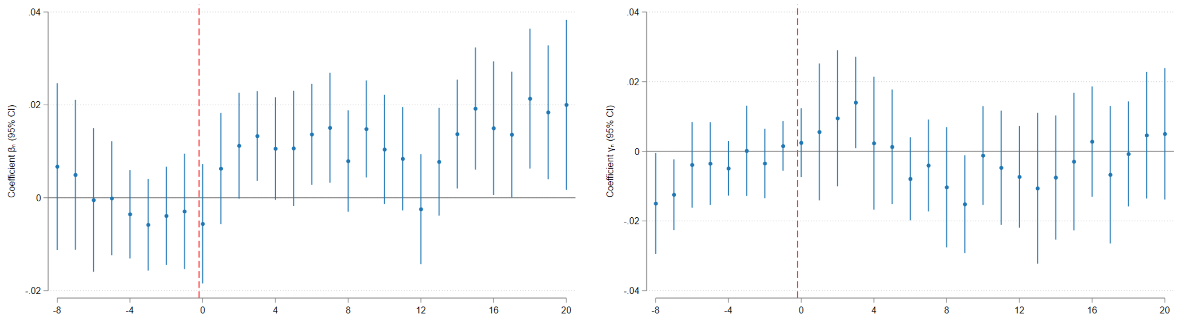
(b) Proximity to new standard

Figure C.4: RESULTS FOR THE BOOK-VALUE OF THE FIRM CONTROLLING FOR SSO MEMBERSHIP



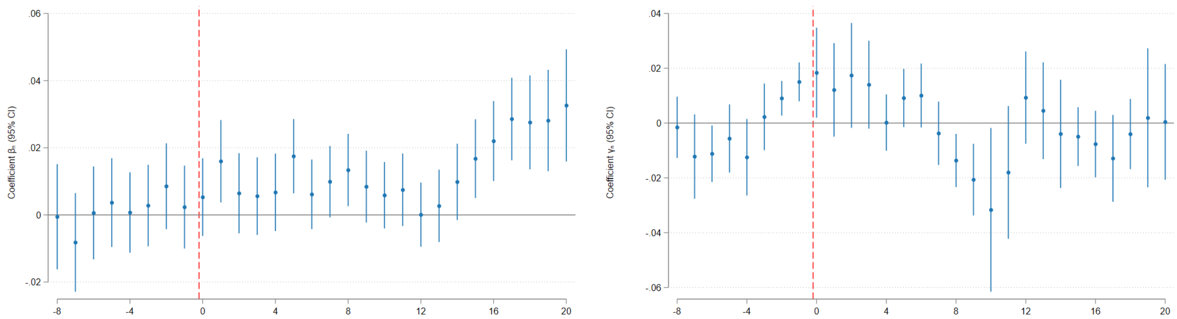
(a) Patent quality (b) Proximity to new standard

Figure C.5: RESULTS FOR THE NET-WORTH OF THE FIRM CONTROLLING FOR SSO MEMBERSHIP



(a) Patent quality (b) Proximity to new standard

Figure C.6: RESULTS FOR THE MARKET-VALUE OF THE FIRM CONTROLLING FOR SSO MEMBERSHIP



(a) Patent quality (b) Proximity to new standard from patents matched to US standards. Finally, we re-estimate the empirical models of Section 3.2. As shown in Figure C.7(a)-C.9(b), results still hold. On the other hand, when considering only standards issued by US SSOs to build the proximity measure, the effect of standardization on each dependent variable is null or it exhibits a pre-trend.

C.4 Main results under different definitions of markets

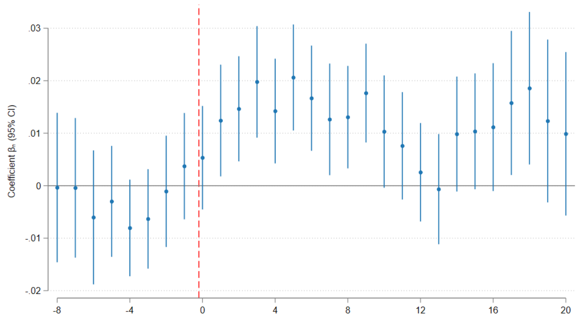
In Section 3.2 we define markets at the NAICS3 industry-level. Yet, this definition can be to broad. To assure that our results do not depend on this, here we use data from Hoberg and Phillips (2010) and Hoberg and Phillips (2016) to build clusters of firms marketing similar products.[11] As shown in Figure C.10(a)-C.12(b), results hold also in this case.

C.5 The different contribution of innovation and diffusion for manufacturing and high-tech firms

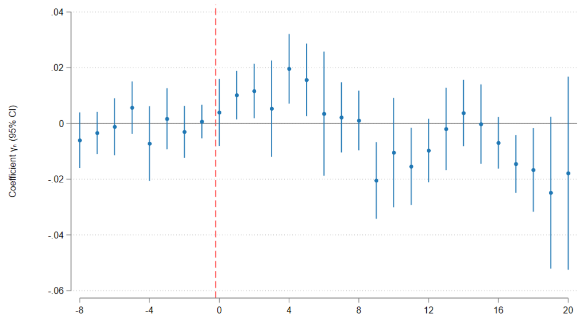
Here we split the results of Section 3.3 by manufacturing and high-tech firms. As shown in Figure C.14b-C.16b, results are mostly explained by firms operating in the manufacturing sector.

[11] In detail, we build groups of product-based competing firms by using the clustering definition of 1995.

Figure C.7: RESULTS FOR THE BOOK-VALUE OF THE FIRM WHEN EXCLUDING AMERICAN SSOS

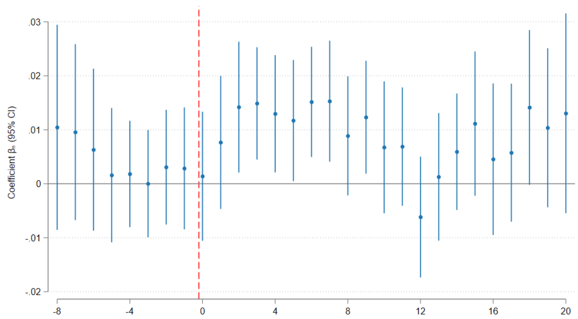


(a) Patent quality

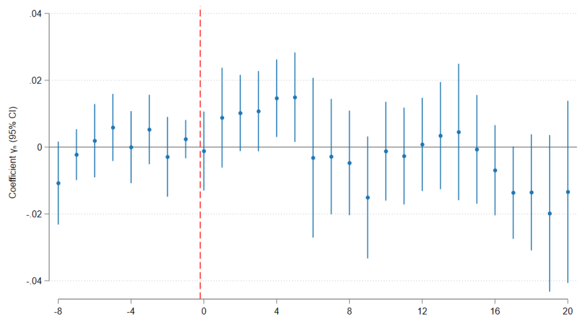


(b) Proximity to new standard

Figure C.8: RESULTS FOR THE NET-WORTH OF THE FIRM WHEN EXCLUDING AMERICAN SSOS

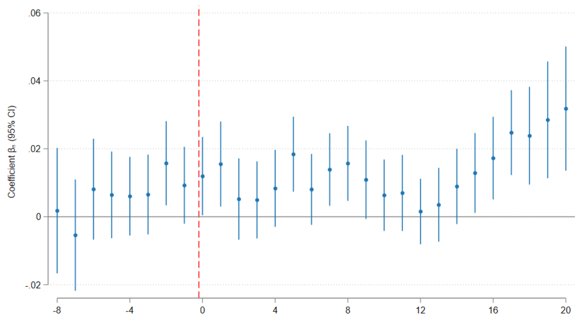


(a) Patent quality

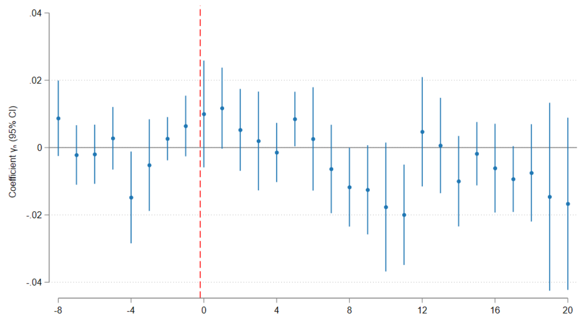


(b) Proximity to new standard

Figure C.9: RESULTS FOR THE MARKET-VALUE OF THE FIRM WHEN EXCLUDING AMERICAN SSOS

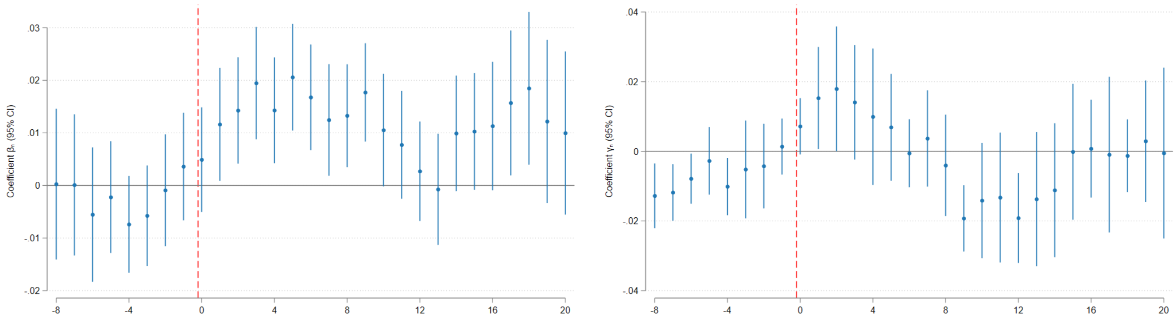


(a) Patent quality



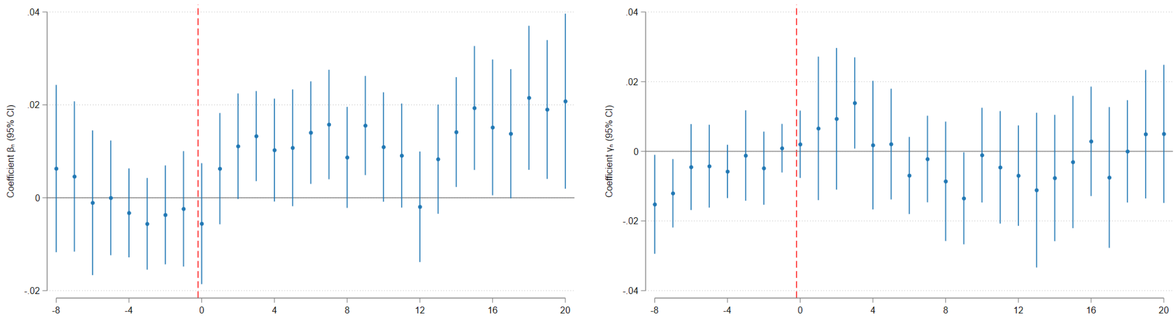
(b) Proximity to new standard

Figure C.10: Results for the Book-value of the Firm under product market clustering



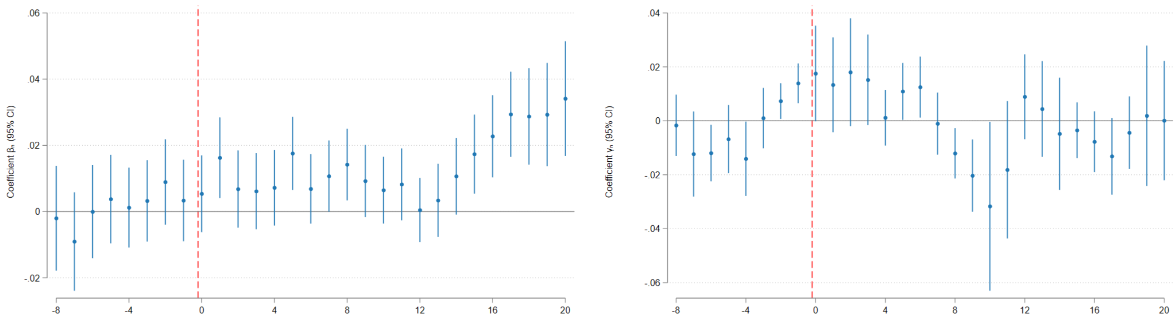
(a) Patent quality (b) Proximity to new standard

Figure C.11: Results for the Net-worth of the Firm under product market clustering



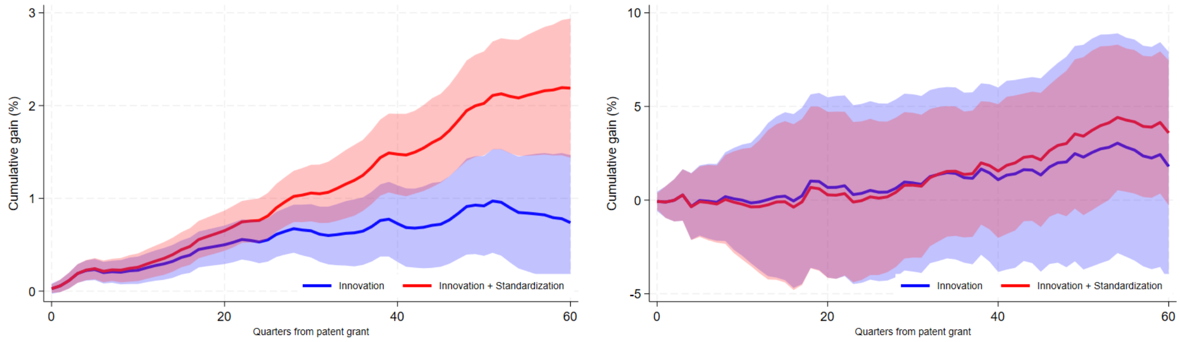
(a) Patent quality (b) Proximity to new standard

Figure C.12: Results for the Market-value of the Firm under product market clustering



(a) Patent quality (b) Proximity to new standard

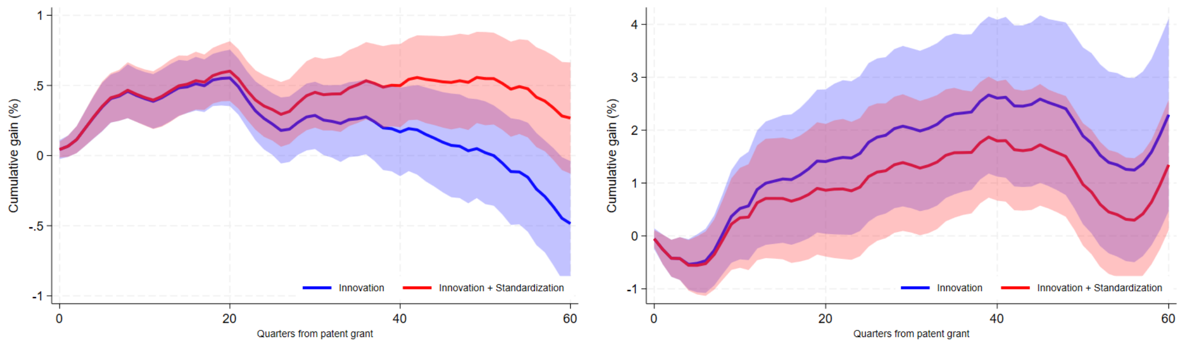
Figure C.13: RESULTS FOR THE BOOK-VALUE OF THE FIRM



(a) Manufacturing

(b) High-tech.

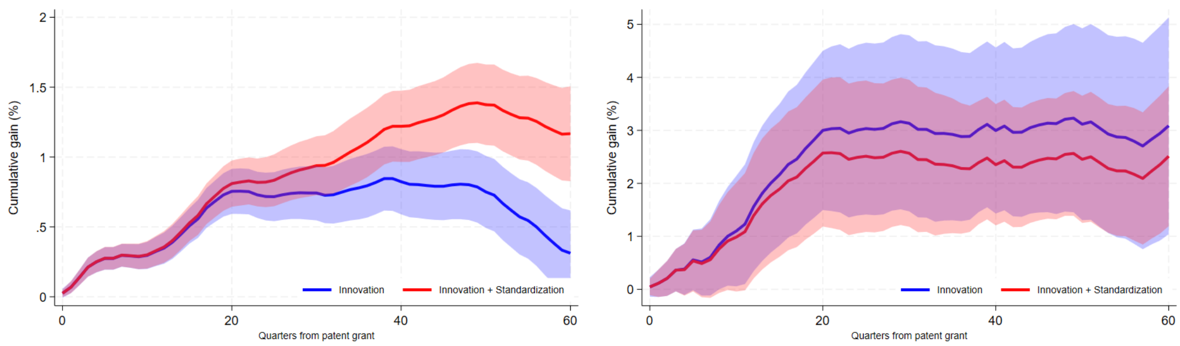
Figure C.14: RESULTS FOR THE NET-WORTH OF THE FIRM



(a) Manufacturing

(b) High-tech.

Figure C.15: RESULTS FOR THE MARKET-VALUE OF THE FIRM



(a) Manufacturing

(b) High-tech.