Patents that Match your Standards: Firm-level Evidence on Competition, Innovation and Growth[⋆]

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Abstract

When a technology becomes the new standard, the firms that are leaders in producing this technology gain a competitive advantage. Matching the semantic content of patents to standard documents, we show that firms closer to the new technology standard increase their market share and sales. In addition, if they operate in a competitive market, these firms also increase their R&D expenditure. Yet, these effects are temporary since standardization creates a common technological basis for everyone, which allows followers to catch up and the economy to grow.

Keywords: Standardization, Patents, Competition, Innovation, Growth, Text mining
JEL: L15; O31; O33

1. Introduction

The development and production of goods and services is often subject to a myriad of technical standards. From payments systems to specifications for doorframes or autonomous vehicles, industrialized societies rely heavily on technical standards in every sector of the economy. By defining a common set of rules, guidelines and specifications, standardization guarantees the interoperability of devices, compatibility of inputs, or the safety and quality of products at the benefit of both producers and consumers. Technological standardization inherently involves the selection of one technology over others as it aims to ensure the widespread proliferation of the best technologies and practices within each industry. This is achieved by requiring industry participants to align on a common set of rules, thereby limiting the proliferation of potentially incompatible alternatives.

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Yet, a firm's ability to adapt to a new standard hinges on its past strategic decisions. Certain firms, given their innovation history, may be better technologically equipped to implement the requirements and processes described in the recently issued standard. Consequently, firms that have already knowledge and expertise in the technology described by the new standard could gain an immediate competitive advantage and benefit from a shift in market power in their favor. This raises a well-known trade-off between rewarding successful innovations and preventing the emergence of monopolies.

This paper contributes to this ongoing debate by studying the firm- and sector-level consequences of large-scale technology adoption. The process of technological standardization offers an opportunity to examine these questions. By introducing a novel measure of firm-level proximity to technology standards, we show how the selection of one technology among competing ones through standardization affects competition, innovation, and growth. Despite an important literature in industrial organization on standardization, the macroeconomic literature has so far overlooked this issue which is essential to the process of innovation and technology adoption.

To address the above question empirically, we combine (i) knowledge of which technologies have been adopted by an entire industry and (ii) the innovative activity of individual firms. For the former, we rely on the fact that large-scale technology adoption usually requires industry participants to coordinate on a set of common rules, a process formally known as *standardization*. For this we use documents approved by industry experts from Standard-Setting Organizations (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. For the latter, we use patent data which is a widely used measure of innovation at the firm level (see Hall et al., 2005). Hence, we match the semantic content of patents to standard documents and can express the proximity of a patent to each standard by evaluating to what extent their content overlap. Aggregating across firms' patent portfolios, we are able to measure a firm's proximity to the new technology standard. This allows us to characterize in detail firms' responses to standardization and to provide new evidence on its macroeconomic implications.

Our results show that, in response to the release of a new standard, firms that own patents closer to the newly selected technology have an immediate competitive advantage that translates into higher sales and market shares. We also find that, if the market is competitive, these firms invest more in R&D while this is not the case if the level of competition is low. Our results are consistent with the interpretation of standardization as a reduction in the level of competition in the short-run, benefiting *technological leaders*.[1] However, this advantage is not permanent. Indeed, the objective of standardization is to establish a common framework that allows the rest of the industry to catch up over time through spillovers. We show that this mechanism has a positive long-term effect on sectoral growth. Contrary to creating enduring monopolies or fostering rent-seeking behavior, standards stimulate competition and innovation across the industry and contribute to long-term

[1] A standard need not necessarily mirror the most radical or groundbreaking technologies in the market. However, its essential purpose is to forge a unified framework of rules and practices, poised to become preeminent best practices. Consequently, firms able to swiftly implement these technologies can indeed be considered as technological leaders.

economic growth.

Our analysis proceeds as follows. First, we apply a semantic algorithm to measure the proximity of every patent to every standard. In particular, we use the fact that each standard is associated with a set of relevant keywords that can be directly compared to the information in patent abstracts. From this procedure, we are able to link 7.5 million US patents to about 0.65 million standards and evaluate the semantic similarity between each pair. This new measure represents a substantial novelty as most of the literature focuses on either patent data to measure innovation at the firm level (e.g. see Griliches, 1990 and Hall et al., 2005), or standards data to measure technology adoption at the industry level (e.g. see Baron and Schmidt, 2014). Our measure correlates with the economic value of patents (defined as in Kogan et al., 2017), their scientific value (measured by forward patent citations) and their private value (patent holders are more likely to pay renewal fees). Yet, it spans beyond those attributes: it identifies patents that, within comparable technologies and of similar quality, describe innovations better suited to adapt to the new standard definition. For the firms owning these patents, this entails both the diffusion of their technologies as well as their capacity to quickly deploy, scale and market new applications of the standard.

In the second part of our investigation, we analyze the firm-level implications of owning patents close to new standards. Specifically, we use the crosswalk from Kogan et al. (2017) to match firm-level quarterly data from Compustat, Crisp and Ibes to patent data and to our new measure of technological proximity that we aggregate at the firm-quarter level.

As a first exercise, we analyze the validity of our firm-level proximity measure. In fact, if a certain technology is already widely used in an industry (ex-post standardization), our measure would correctly capture successful innovations, but not the additional impact of standardization. To investigate this point, we study the information content of our proximity measure by looking at the stock market reaction that follows the release of a new standard. We find that financial market participants indeed respond to standardization by revising upward earnings expectations for firms closer to the standardized technology. The revision occurs only at the time when the content of the standard is made public and despite the fact that the firm's patent portfolio is already known. Moreover, firms closer to the new standard exhibit abnormal returns in the same period. These results suggest that the specific content of a standard, and consequently the relative proximity of each firm to the standard, represents a surprise for markets. This is an important point as it implies that –despite the process of standardization being endogenous– the approval of a new standard is a necessary step for firms to deploy, scale and market their innovations. Stock markets pick up these effects by revising growth opportunities for firms closer to the standardized technology. Furthermore, the disclosure of a standard unveils additional insights into a patent's potential to enhance a firm's market value, surpassing the initial estimations made at the time of the patent grant as measured by Kogan et al. (2017).

As a second exercise, we show that firms closer to the new standard indeed gain both in terms of sales and market shares only after the publication of the standard itself. These effects are not anticipated and last for roughly five consecutive quarters. In particular, we estimate that –for these firms– this translates into an (average) increase of sales and market share by 2.0%. Thereafter, to shed light on the interplay between competition and innovation, we consider the responses of investment in R&D following standardization, which depend on market structure. Specifically, we find that if a firm is operating in a competitive (non-competitive) market and is close to the technology standard, it will invest more (less) in R&D after the release of the standard. This is consistent with the literature that has emphasized a non-linear relationship between competition and innovation (see Aghion et al., 2005). Overall, for the entire sample of firms, the expansion of R&D is the prevailing effect. We estimate that, on average, firms close to the new standard increase their investment in innovation by 4.8%. In light of this, we can interpret the release of a standard as a temporary shift in competition in favor of those firms better equipped to immediately adopt and deploy the standardized technology.

Our identification could be affected by various potential threats. Most importantly, it is possible that some firms lobby or exercise undue influence over SSOs to push for the inclusion of their patents into the new standard (Bekkers et al., 2011; Farrell and Simcoe, 2012). If this is the case, our proximity measure would capture the lobbying power of a firm rather than its innovative capacity. To check this, we perform two tests. First, we use SSO membership data to control that results are not driven by the direct participation of firms in the standardization process. Second, we exclude standards developed by US SSOs from the calculation of our proximity measure as it is more likely that US firms have stronger influence at national level. Moreover, our results might be driven by mismeasurement. In particular, our measure of proximity could reflect the patent portfolio size or the technology field in which the firm operates rather than the quality of its patents. In light of this, we perform a series of exercise showing that our measure is indeed capturing the quality of a patent and its proximity to a standard, and that it is this quality dimension that drives our results. For example, we construct a number of counterfactual proximity measures, keeping the same set of patents at the firm level but randomizing their score with standards. We show that these placebos generate no effect.

Finally, we explore the aggregate implications of standardization for growth and competition. Our findings suggest that while standardization confers a significant advantage to firms closer to the standardized technology (which we consider as the technological leaders), this effect is short-lived. In the long-run, standardization promotes knowledge spillovers and wider technology dissemination, indicated by a growing number of patent citations from other firms to patents of the leading firms and an increasing production of new patents that converge in content to the just published standard. This dynamic allows these firms to catch up with leaders, thus contributing to overall growth in the sector. Notably, four years after a standard's introduction, we observe an increase in sectoral growth by 0.2 percentage points, mostly driven by the industry-wide catch-up process. This process boosts also sectoral competition. In fact, sectoral concentration declines in the long-run following the introduction of a standard.

In light of this evidence, this paper contributes to the policy debate on the link between competition and innovation and its implications for economic growth. Standardization and its consequences represent an important and overlooked dimension to study this question. On the one hand, proponents of standardization argue that it is both an acknowledgment of the best technology among competing ones, and also a way to speed up the diffusion of this technology and subsequent improvements. On the other hand, the release of a standard can lock a certain industry in the chosen technology. This might prevent the emergence of competing technologies by transferring substantial market power to firms that have a considerable stake in the standardized technology. Not surprisingly, the policy debate among regulators and standard-setting organizations has centered around this complex trade-off (Lerner and Tirole, 2015).

Related literature. Our study relates to different strands of the literature.

The first one is on technological standardization which has received much attention in the industrial organization (IO) literature, but remains largely overlooked in macroeconomics despite the omnipresence of standards in every aspect of economic activity (see Kindleberger, 1983 for an historical overview). The IO literature has identified a wide range of benefits of standardization. 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 deployment of inventions and technologies. In order to reap the benefits of standardization, technological specifications and details must be agreed upon by industry participants. Standard-setting organizations (SSOs) are fundamental in that process (Rysman and Simcoe, 2008).

Consequently, standardization is an essential prerequisite 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 (see Baron and Schmidt, 2014, who exploit the timing of standard releases to study the business cycle implications of technology adoption).

The benefits of standardization notwithstanding, several concerns have been highlighted in the literature. With the arrival of new technologies, the optimality of the incumbent standard is called into question. However, high switching costs may prevent the adoption of new technologies such that industries become "locked in" a certain standard (Farrell and Klemperer, 2007; Farrell and Saloner, 1986). The QWERTY keyboard is an often cited example of such a lock-in effect as consumer habits and compatibility prevent the adoption of more efficient keyboards such as DVORAK (David, 1985).

Another related concern is that standards, by favoring one technology over another, can give too much market power to the owners of the technology in question, especially if its use is safeguarded by patent protection. It is for this reason that SSOs insist that holders of so-called standard-essential patents (SEPs) respect fair, reasonable and non-discriminatory (FRAND) licensing principles. This loose prescription has led to an intense debate among regulators, economists and lawyers, and to a theoretical literature on the optimal design of rules on standard development, SEP licensing or voting procedures (Lerner and Tirole, 2015; Schmalensee, 2009; Llanes and Poblete, 2014; Spulber, 2019).[2]

Contrary to the IO literature, we abstract from questions such as the microeconomic process of standard development or rules setting in SSOs. We take the standardization process as given and focus on its macroeconomic implications. We aim to evaluate whether the beneficial aspects of the large-scale diffusion of new technologies through standardization can outweigh the potentially detrimental aspects that may arise when some firms acquire too much market power and future innovation is impeded. While we measure the

[2] While empirical studies have used data for selected SSOs for which SEP declarations are available (Bekkers et al., 2017; Baron and Pohlmann, 2018), true standard essentiality is often questioned and problems of both over-declaration and under-declaration may arise (see the discussion in Brachtendorf et al., 2022).

proximity between patents and standards, our measure is not confined to the standard essentiality of patents. On the contrary, we consider all patents that indicate whether a firm has knowledge and expertise in the field that is covered by the standard. We cover the universe of standard and patent documents and not just those that are linked through declared standard essentiality. Importantly, our measure covers all sectors of economic activity and not only ICT which is the industry that the IO literature usually focuses on.

The second strand of literature this paper speaks to concerns the link between innovation and competition. In endogenous growth models (in particular Romer, 1990; Aghion and Howitt, 1992; Grossman and Helpman, 1991), an increase in the level of competition should reduce the incentive to innovate as it also reduces future rents. However, as surveyed in Aghion and Griffith (2005), this prediction is not very clear in the data. This motivates the authors to emphasize the non-linear relationship between competition and innovation: while competition can still dampen innovation, it also induces firms to intensify their innovation activities in order to escape competition. Empirically, a number of papers have looked at the reaction of innovative firms to competition shocks, often using trade shocks (Autor et al., 2020; Aghion et al., 2018; Bloom et al., 2016; Iacovone et al., 2011; Aghion et al., 2021; Akcigit et al., 2018). To the extent that patents give a temporary monopoly power to its assignee and that standards lock a whole industry in a given technology, then standardization leads to a reduction of competition if the underlying technology is owned by a small number of firms. Our paper therefore contributes to this empirical literature by considering a more direct measure of competition and allows to look at the impact of a change in the degree of competition at the firm and aggregate level. Moreover, when looking at the aggregate implications of standardization, our findings corroborate results from the theoretical literature on the role of standardization (Acemoglu et al., 2012), technological adoption and diffusion (Benhabib et al., 2021, Perla and Tonetti, 2014) which stresses the importance of the catching-up effect of technological laggards for growth.

We also study the information content of standardization. In particular, we relate to a literature that studies how financial markets react to innovation-related corporate events. For example, Eberhart et al. (2004), Chan et al. (1990) and Szewczyk et al. (1996) show that firms exhibit positive abnormal returns and higher share value when the management announces an unexpected R&D investment plan. Similar results are found in Kogan et al. (2017), Pakes (1985), Nicholas (2008) and Austin (1993), who show that markets positively reacts to news on patenting activity.[3] All these papers demonstrate that the market efficiency hypothesis (see for example Daniel et al., 1998, Mitchell and Stafford, 2000) holds also when information on corporate innovation activity is disclosed: markets are able to correctly understand and discount what the future benefits of innovation will be. Our paper shows that this is the case also when information on a new standard is released.

Finally, our work contributes to the literature on text-mining applied to the semantic analysis of patents and standards. Looking at the standard-essentiality of patents, Brach-

[3] In a similar vein, Ma (2021) uses patent data to construct measures of technological obsolescence and analyzes earnings forecasts and stock returns in response to the obsolescence of a firm's innovation portfolio.

tendorf et al. (2022) use text mining techniques to match patents to standards.[4] Contrary to their paper, we concentrate on the universe of standards released by a large variety of SSOs and are interested in how standardization affects real outcomes at the firm and macroeconomic level. 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) or to classify patents (Bergeaud et al., 2017; Webb et al., 2018; Argente et al., 2020). The content of patent publications has also been used to construct measures of novelty based on the amount of textual dissimilarity from previous patents and high similarity with subsequent ones as done by Kelly et al. (2021).

The paper is organized as follows: Section 2 briefly describes the matching procedure and the construction of the data; Section 3 looks at how standardization relates to indicators of patent quality; Section 4 presents our firm-level results and link our results with the theoretical literature on innovation and competition; Section 5 discusses the aggregate implications of our results; Section 6 concludes.

2. Data construction and matching

2.1. Data sources

Patent data. A patent is an exclusive right granted to an inventor or an assignee for an invention in exchange for the disclosure of technical information. For the matching procedure, we use all US priority applications that are available in the `IFI CLAIMS` database from 1980 to 2020, without restrictions on the technological field.[5]

The `IFI CLAIMS` database contains 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 restrict our sample to patents filed between years 1980 and 2010. This corresponds to over 7.5 million observations on the patent-level.

Standard data. 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

[4] Specifically, they use SEP declarations for one specific SSO, namely ETSI (European Telecommunications Standards Institute), to evaluate the true standard essentiality of patents. The *Semantic similarity of patent–standard pairs database* described in Brachtendorf et al. (2020) considers standards not only from ETSI, but also from IEEE and ITUT.

[5] Patents are grouped into families which include different publications that are more or less related to the same invention. More precisely, during a 12-month period following the filing of an application, the applicant has a *right of priority* meaning that during this period, she can file a similar patent in a different patent office and *claim the priority* of the first application. If the priority claim is valid, the date of filing of the first application is considered to be the effective legal date for all subsequent applications. All the patents sharing a similar *priority application* define a family. The priority application is the first patent in a family (see Martinez, 2010 for more details).

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*.

To collect information on 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 (usually professionals) with basic information on the standard and the possibility to purchase the access to individual standard documents. Our database covers all types of standards that have been released in a large number of industrialized countries. The `Perinorm` database also contains keywords describing each standard. These keywords were provided by `Perinorm` experts when including standards into their database to facilitate the search for specific standards by its users. They represent one of the main ingredients for our matching procedure.

We clean the standards data as follows. First, we regroup standard documents that are equivalent. Indeed, a single standard can be released several times, for example once by a French SSO and once by a German SSO. To avoid keeping duplicates, we regroup those standards and create a database in which we store the standards group identifiers, the standards contained in the group, their ICS (International Classification of Standards) and the earliest date of publication. We end up with a sample of 0.65 million standards. Finally, we store the keywords associated to the standards of the group. More details are provided in Appendix A.

2.2. Semantics-based matching of patents to standards

Matching procedure. We start by processing the keywords that have been provided by `Perinorm` experts for each standard. We first clean these keywords using common techniques used in text-mining (such as removing upper-case letters, special symbols, punctuation or stop words such as *the*, *at*, *from*, etc.). We then form k-grams, i.e. a sequence of k words that we consider as a unique entity (i.e. the 2-gram *air condition* is not the same as considering *air* and *condition* separately). We stem these k-grams which consists in only keeping the "root" of the keyword (i.e. *fertilizing* and *fertilizer* become both *fertiliz*). As a result, we obtain a database where each standard is associated with a list of k-grams.

Then, we proceed similarly and extract keywords from the patent abstracts, form and stem k-grams, and keep those that are in the list of standards keywords. Thus, we obtain a database where each patent and standard is listed with their associated k-grams. We calculate the so-called *inverse document frequencies* for each k-gram in our respective database of extracted standard and patent k-grams. This will allow to assign them an importance weight.[6] We only keep k-grams that do not appear in more than 1 out of

[6] The inverse document frequency is based on a measure of how often a word shows up in a database

500 standards or 1 out of 1000 patent documents. Then, we register all patent-standard combinations which share the same k-gram on the k-gram-level along with the term-frequency (i.e. number of repetitions) of each k-gram in the patent abstract. Then a score of bilateral proximity between each patent and standard is computed. In particular, the score is defined using the cosine similarity between standard i and patent j:

$$Score(i,j) \equiv \frac{\mathcal{A}(i)\cdot\mathcal{B}(j)}{\|\mathcal{A}(i)\|\ \|\mathcal{B}(j)\|} = \frac{\sum_{k=1}^{K}\mathcal{A}(i)_k\mathcal{B}(j)_k}{\sqrt{\sum_{k=1}^{K}\mathcal{A}(i)_k^2}\cdot\sqrt{\sum_{k=1}^{K}\mathcal{B}(j)_k^2}}$$

where $\mathcal{A}(i)_k$ and $\mathcal{B}(j)_k$ are the k-th components of vectors $\mathcal{A}(i)$ and $\mathcal{B}(j)$, which represent the weighted occurrence of k-grams in standard i and patent j, respectively. The vectors span the union of all k-grams found in either document: $\mathcal{K} = \{\mathcal{A}(i) \cup \mathcal{B}(j)\}_{i,j}$.

To account for the informational value of each term, we define:

$$\mathcal{A}(i)_k = IDF(w_k^A) \quad \text{and} \quad \mathcal{B}(j)_k = IDF(w_k^B)\cdot TF(w_k)$$

where $IDF(w_k^A)$ and $IDF(w_k^B)$ denote the inverse document frequency of keyword w_k across the corpus of standards and patents respectively, and $TF(w_k)$ is the term frequency of w_k within the patent abstract. The combination of TF/IDF and cosine similarity is commonly done in the literature (e.g., Seegmiller et al., 2023, Kelly et al., 2021), and it ensures that rare but salient terms occurring repeatedly in the patent abstract are given greater weight in measuring textual similarity (see Appendix B.1.2 for details).

This matching procedure results in more than 1.1 billion patent-standard combinations. For reasons of computational power, we need to restrict the number of patent-standard matches that we use for our empirical analyses in Sections 3 and 4. We therefore extract the best 100 million matches. This choice of 100 million is admittedly arbitrary, but is consistent with the highly skewed distribution of the scores. Appendix B describes the matching procedure in detail and provides an example of matching of two different patents to a standard. In Appendix B.2 we also show that our matching procedure maps well the broad categories of the IPC (patents) and ICS (standards) classifications.

Sample selection. Based on the extraction of the first 100 million matches, we consider only observations of unmatched and matched patents that have been filed before the publication of the standard. Table 1 reports summary statistics of the final sample that we use in our econometric analysis of Sections 3 and 4. The sample is composed of 64.5 million patent-standard matching pairs. The average similarity score from a patent-standard match is 0.24 and the distribution of scores is particularly (left) skewed. This is an important feature of our patent-level data as such skewness implies that most patents do not match or match a standard poorly. In fact, the average patent matches 7.5 standards from the moment of the patent filing onwards, although 75% of patents do not match any standard. If the match occurs, the mean time-lag between patent filing and following

of documents. See Appendix B for details.

Table 1: DESCRIPTIVE STATISTICS OF THE MATCHING PROCEDURE

	Mean	*SD*	*Min*	*Max*	*p1*	*p5*	*p25*	*p50*	*p75*	*p95*	*p99*	*N*
Final sample:	unmatched and matched patents with filing year < standard release year											
Score	0.24	0.15	0.00	1.00	0.00	0.00	0.16	0.21	0.29	0.50	0.73	64,488,773
Time lag	12.36	8.69	0.00	38.00	0.00	1.00	5.00	11.00	18.00	29.00	34.00	57,556,532
Standards	7.65	47.48	0.00	1778.00	0.00	0.00	0.00	0.00	0.00	22.00	224.00	7,521,262

Notes: The table reports descriptive statistics for the score, the number of matched standards per patent and the time lag (in years) between the release of the standard and the filing of the patent. The sample only comprises utility patents, matched and unmatched, for which the patent filing date does not exceed the standard release date. The number of observations in the row reporting time lag statistics is lower than in the row reporting score statistics, as the latter also includes unmatched patents for which, by definition, no time lag data is available.

standard release is 12 years.[7] For this sample, we plot the distribution of scores across ICS classes in figure C.1(a) of Appendix C. Contrary to the IO literature which concentrates on ICT, our patent-standard matching covers all technologies and sectors. The distribution is not dominated by a single ICS class.

2.3. Firm-level data

Aggregation of scores at the firm level. We use the mapping provided by Kogan et al. (2017) to associate each patent to the Compustat firm that filed it.[8] Given the mapping between patents 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. Formally, define J as the set of all IPC classes such that $j \in J$ is a specific IPC class, and call $Score_{i,p,j,t}$ the score obtained by firm i when matching patent p that belongs to the IPC class j and was issued prior to the standard publication date 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:

$$Tech.Prox_{i,t} = \sum_{j \in J} \omega_{i,j,t_0} \sum_{p \in j} \zeta^{(t-\underline{t}_p)} Score_{i,p,j,t}$$

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. $\zeta = (1 - \delta)$ is a discount factor that takes into account depreciation of the score generated from the match of patent p (filed at time $\underline{t}_p < t$) and standard j (published at time t). Following Madsen (2010), we set δ to match the annual rate of 20%. By factoring in depreciation, the aggregation of scores will give less

[7]In Appendix C, we show that, when considering patents filed either before or after the publication of a standard, we find that a large number of patents matched to a standard actually follow the release of the standard itself. In other words, standardization may lead to more patenting if the standardized technology leads to follow-up innovation. Such standard-induced innovation is a specific aim of SSOs: by defining common rules for the design and use of an *underlying* technology, firms are incentivized to invest into the technology and develop marketable applications and products.

[8]More precisely, we use an updated version of Kogan et al. (2017) taken from their Github repository.

weight to high scores from old patents. Consequently, we do not give much importance to technologies that –despite being relevant for the current standard– potentially could have already diffused over a longer horizon prior to the standard release. By doing so, our proximity measure limits the possibility of capturing ex-post standardization. Moreover, depreciation mitigates the role of patent portfolio size, which could potentially inflate the aggregation of scores throughout time as the number of patents increases.[9]

To sum up, the variable $Tech.Prox_{i,t}$ is a firm-quarter level continuous variable expressing the (IPC-weighted) proximity of the stock of patents (accumulated until t) of a firm to the standards released in 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 $Tech.Prox_{i,t}$ the closer the firm's portfolio of patents to the newly released standard.[10] In Section 4.5, we provide evidence that this variable is not just a by-product of the type of the firm innovation activity (for example favoring some IPC classes against other), or the quantity of innovation and size of the portfolio of patents, but it is indeed capturing the effective proximity of firms' patents to the new standard. In Appendix C (Figure C.1(b)), we show the distribution of $\mathbb{I}[Tech.Prox > 0]$ across ten broad NAICS industries: the most representative sectors are mining and manufacturing which explain respectively 20% and 17% of all positive proximity values.

Balance sheet data. We use firms' balance sheet data from Standard&Poor's Compustat to build all (real) dependent and control variables used in the empirical analysis of Section 4. The dependent variables under consideration are: sales, R&D investment and market share. Sales are the revenues of the firm as reported at the end of the quarter in the income statement. As it is under-reported or reported only in the last quarter of the year, we do the following correction for R&D expenditure: we distribute the annual expenditure evenly across all four quarters to ensure that the sum of reconstructed quarterly values matches the reported annual figure. For comparability across firms, we normalize these two variables by the (mean) level of fixed assets (property, plant, equipment).[11] The last variable of interest is the market share of the firm, defined as the ratio of firm-level sales over the total volume of sales in a NAICS 3-digit industry (NAICS3). In a robustness check, we also construct market shares using the product market classification of Hoberg and Phillips (2010).

Along with these variables, we follow Chan et al. (1990) and consider also: 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), market capitalization (in billions of USD). Finally, we use data on firm-level markups from De Loecker et al. (2020) to construct a measure of sectoral competition based on within-industry markup dispersion (see in this

[9]Varying the level of depreciation does not affect the results presented in the following sections.

[10]We normalize this measure by the maximum observed value in its distribution such that it ranges from 0 to 1. It is equal to 0 for more than half of the sample. See Table 2 for more details.

[11]As we show in Bergeaud et al. (2022), the value of assets is sensitive to the proximity measure. For this reason, we prefer to normalize sales, capital investment and R&D with the mean-level of fixed assets rather then with the contemporaneous level or some lag. By doing so, the change in the numerator of the ratio is not influenced by the change in the denominator.

regard Edmond et al., 2015, Mrázová et al., 2021 and Traina, 2018). This information allows to understand which industry is (on average) less or more competitive, i.e. has a higher or lower markup dispersion, and consequently which firms operate in a less or more competitive market. We define a firm as belonging to a non-competitive market if the average markup dispersion of its corresponding NAICS3 industry is above the 75^{th} percentile of the distribution.

Financial market data. As explained in Mitchell and Stafford (2000), abnormal returns are useful to study short-term market reactions to corporate events. Following this line, we want to evaluate how markets interpret the standardization event. Since our analysis focuses on the real effects of technological proximity within a NAICS3 industry, we calculate abnormal returns at that level of disaggregation. Here, we describe the procedure of extrapolation. First, we match Compustat with data from the Center for Research in Security Prices (CRSP). Then, for each NAICS3 industry, we build the returns of a portfolio composed of all firms listed in that industry. Formally, given the number of firms I_t belonging to the NAICS3 industry s at time t, the return on the industry s portfolio can be written as $r^s_t = \sum_{i=1}^{I_t} x^s_{i,t} r_{i,t}$ where the weight $x^s_{i,t}$ is equal to the relative market capitalization of firm i in industry s at time t. Hence, we estimate a statistical model which differs from the baseline Capital Asset Pricing Model (see Jensen et al., 1972) only for the definition of the market portfolio, here defined at industry-level. Formally –given information on the 3-month T-bill rate (r^f_t) and the return on each industry portfolio (r^s_t)– for every firm i belonging to industry s and 10-year (40-quarter) rolling window with ending period τ, our asset pricing model is:

$$r_{i,t} - r^f_t = \alpha_{i,\tau} + \beta_{i,\tau}(r^s_t - r^f_t) + \varepsilon_{i,t}, \ \ \forall t \in (\tau - 40, \tau]$$

with $\varepsilon_{i,t}$ being the error term. Then, we use the OLS estimates $\widehat{\alpha}_{i,\tau}$ and $\widehat{\beta}_{i,\tau}$ to predict the firm's (excess) return one quarter after the end of each 10-year estimation window, i.e. in period $\tau + 1$. Finally, we define the abnormal return ($ar^s_{i,t}$) of a firm i from industry s as the difference between the observed and predicted (excess) return:

$$ar^s_{i,\tau+1} = (r_{i,\tau+1} - r^f_{\tau+1}) - \left(\widehat{\alpha}_{i,\tau} + \widehat{\beta}_{i,\tau}(r^s_{\tau+1} - r^f_{\tau+1})\right).$$

We repeat this procedure for each firm i in the sample and for all available 10-year rolling windows with ending period equal to τ, $\tau + 1$, $\tau + 2$, ..., $\tau + T$.

In addition, we match Compustat to data from the Institutional Brokers' Estimate System (IBES). From this dataset, we collect professional analysts' expectations over the future Earning-Per-Share (EPS) ratio of the firm. In particular, we look at how forecasters expect the EPS to be at the end of the following fiscal year. In fact, by considering a fixed forecasting horizon, we can study how expectations change over time as the end of the fiscal year approaches. Therefore, for each firm and quarter, we take the mean of the 1-year EPS forecast across all professional forecasters, and obtain a measure of market expectations over the future economic performance of the firm.

Sample selection. We follow Brown et al. (2009) and exclude all regulated utility and financial firms as well as firms with missing assets. Then, we match the remaining

Table 2: DESCRIPTIVE STATISTICS FOR THE FIRM-LEVEL DATA

	Mean	*SD*	*p1*	*p5*	*p25*	*p50*	*p75*	*p95*	*p99*	*N*
(A) Proximity Measure										
$Tech.Prox$ (*in percent*)	0.46	2.24	0.00	0.00	0.00	0.00	0.02	1.94	7.87	24,162
$\mathbb{I}[Tech.Prox > 0]$	0.48	0.49	0.00	0.00	0.00	0.00	1.00	1.00	1.00	24,162
(B) Firm Characteristics										
Sales	0.62	0.72	0.01	0.08	0.25	0.47	0.78	1.60	2.99	24,162
R&D	0.05	0.29	0.00	0.00	0.00	0.01	0.05	0.18	0.59	24,162
Market Share (*NAICS*3)	0.05	0.10	0.00	0.00	0.00	0.01	0.05	0.21	0.49	24,162
Age (*quarters*)	98.99	49.92	21.00	21.00	53.00	110.00	137.00	171.00	181.00	24,162
Q	1.93	2.15	0.74	0.90	1.17	1.49	2.12	4.43	8.69	24,162
Leverage	0.19	0.16	0.00	0.00	0.06	0.17	0.27	0.45	0.65	24,162
Market Cap. (*Billion*$)	9.17	28.99	0.00	0.02	0.19	1.27	5.61	42.22	139.98	24,162
Firm Markup	1.46	0.68	0.88	0.98	1.09	1.25	1.57	2.69	4.55	24,162
Industry Markup Dispersion	0.55	0.33	0.14	0.16	0.27	0.48	0.78	0.99	1.44	24,162
$\mathbb{I}$(*Non-Competitive Industry*)	0.25	0.43	0.00	0.00	0.00	0.00	1.00	1.00	1.00	24,162
(C) Financial Mkts										
ar^{NAICS3}	0.00	0.40	-0.58	-0.32	-0.09	0.00	0.08	0.27	0.56	18,531
1yr EPS Forecast ($)	1.67	1.72	-1.07	0.11	0.67	1.32	2.23	4.68	8.39	17,030

Notes: The variable $Tech.Prox$ measures the proximity of the portfolio of patent of the firm to the standard. $\mathbb{I}[Tech.Prox > 0]$ is a dummy that takes value one for positive values of the variable $Tech.Prox$. *Sales* is the firm-level of sales normalized by the mean-level of fixed assets (property, plant, equipment). The *Market Share* is constructed at the NAICS 3-digit level. *R&D* is the level of R&D expenditure normalized by the mean-level of fixed assets. *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. *Market Capitalization* is expressed in Billion of US dollars. The NAICS 3-digit industry markup is constructed following De Loecker et al. (2020). $\mathbb{I}$(*Non-Competitive Industry*) is a dummy that takes value one if a firm is operating in a NAICS 3-digit industry with markup above the 75^{th} percentile. ar^{NAICS3} is a measure of stock market abnormal return built from a standard CAPM model with a NAICS 3-digit index as market portfolio. The *1yr EPS Forecast* is the mean forecast across all professional forecasters of the earning-per-share expected by the end of the following fiscal year, and it is expressed in dollars.

sample of Compustat firms with patent data and our proximity measure. Finally, we keep only firms that are publicly listed, for which all constructed variables are jointly available (except abnormal returns and EPS forecasts), and that have registered at least one patent in their life. By doing so, we end up with a sample of 24,162 firm-quarter observations spanning from 1984 to 2010.[12] Table 2 reports descriptive statistics for this sample. As from panel (A), the proximity measure at the firm-quarter level has a mean equal to 0.46 and a standard deviation equal to 2.24. In our sample, 48% of firms have a positive proximity value. As from panel (B), the average firm has a level of sales and *R&D* equal to 62% and 5% of the value of assets, a market share equal to 5%, it is roughly 25 years old, with a q-value equal to 1.93, 19% of its balance sheet is composed of debt and it has a market capitalization of 9.17 billion USD. The average firm has a markup of 1.46. 25% of firms are from industries with average markup dispersion above or equal to 0.78, and we define these industries as non-competitive. When matching this data with information on abnormal returns and EPS forecasts, the sample is reduced. As from panel (C), our sample contains 18,531 observations on abnormal returns and 17,030 observations on EPS forecasts. The average abnormal return is zero while the average 1-year EPS forecast is 1.67 dollars per share.

[12]In particular, the sample is composed by 892 firms distributed over 60 NAICS3 industries.

3. Innovation and standardization: patent-level results

In this section, we look at the characteristics of patents that are associated with a high score, i.e. patents semantically close to a specific standard. In particular, we compare the computed score with measures of patent quality or economic value.

3.1. Economic value of a patent

Kogan et al. (2017) compute the financial value of a patent based on the stock market reaction to the news of a patent application being granted. This is a forward-looking measure of economic agents' evaluation of the granted patent. While we expect our score to correlate with this measure, there are conceptual differences. While both measures are indicative of the economic value of a patent, our score captures the underlying technology's potential for market-wide adoption or its adaptability to the new standard. It is therefore particularly meaningful to study questions of market share and competition. The economic value à la Kogan et al. (2017) measures markets' perception of the future value of the technology at the time of the patent grant, but potentially abstracts from any future developments and spillovers that are not known at the time of the grant (standardization being one of them).

To relate our score with the economic value of a patent, we use the normalized sum of the score across all associated standards at the patent-level ($\overline{score}_i$) and then run the following patent-level regression:

$$\log\left(\text{value}_i\right) = c + \alpha\overline{\text{score}}_i + \beta\log\left(1+\text{cit}_i\right) + f_{t(i),k(i)} + \varepsilon_i \tag{1}$$

where value_i is the economic value of patent i (in millions USD) from Kogan et al. (2017). We include the number of forward citations cit_i, also taken from Kogan et al. (2017), as a control variable as well as fixed effects $f_{t(i),k(i)}$, namely the interaction of the year and quarter of the grant date of the patent $t(i)$ and its 3-digit IPC class $k(i)$.

Table 3 summarizes the results: column 1 corresponds to the empirical specification that does not control for the number of citations whereas it is added to the model in column 2. Whether we control for the number of forward citations received or not, our aggregated score is positively associated with a higher financial value of the patent and is statistically significant, even within a given technological class in a given year. Results do not change when using the real instead of nominal value of patents or using unweighted counts, i.e. by simply counting the number of associated standards per patent. In order to translate these results into quantitative numbers, we multiply the coefficient of column 2 in Table 3 with the mean of the explanatory variable (0.008) which implies that matched patents are valued 8.6% more. As the median (mean) patent in our sample is valued 7.2 (24.3) mio USD, this translates into a higher patent value by 619,000 (2.1 mio) USD.

3.2. Scientific value of a patent: forward citations

A popular measure of the scientific value of a patent are forward citations (Hall et al., 2005), i.e. citations of the patent in question by subsequent patents. A highly cited patent

Table 3: Regression Results for Financial, Scientific and Private Patent Value

	(1)	(2)	(3)	(4)	(5)
	Kogan et al. (2017)		*Forward citations*	*Expiration*	
Score	10.8471***	10.6565***	3.4686***	-1.5103***	-1.2043***
	[0.299]	[0.289]	[0.082]	[0.074]	[0.059]
Observations	2,283,666	2,283,666	4,374,892	8,806,908	8,806,908

Notes: Patent-level regressions. "Score" is the sum of scores across all associated standards of a given patent (see Section 3.1), normalized to take values between 0 and 1. The dependent variables are: columns 1 and 2: the economic value of the patent as computed by Kogan et al. (2017); columns 3: the number of forward citations received by the patent over a 10 year window; columns 4-5: maintenance decisions for patent i. Columns 1-2 use an OLS estimator, column 3 uses a Poisson model and columns 4 and 5 use a Cox hazard model. Columns 1-2 include a technological class (3-digit IPC) interacted with the granting year/quarter fixed effect as in Kogan et al. (2017). Column 3 includes the 3-digit IPC class interacted with the filing year/quarter fixed effect. Similarly, the Cox model in columns 4 and 5 stratifies the data by the interaction of the 3-digit IPC class with the filing year/quarter. Columns 2 and 5 additionally control for the logarithm of the number of forward citations received by the patent. The sample of patents includes: columns 1 and 2: priority patents from IFI claims matched to the Kogan et al. (2017) sample with filing year between 1980 and 2010; column 3: priority patents from IFI claims published over the period 1980-2010; columns 4 and 5: priority patents from IFI claims matched to USPTO patents with information on renewal fees for the period 1981-2015. In the last two columns, a patent can be included several times in the sample due to different schedules of renewal (see Section 3.3). "*", "**" and "***" designate significance at the 1%, 5% and 10% level.

is used by a larger number of future inventions and therefore signals high technological content and to a certain extent also high economic value.

We extract forward citations from `IFI CLAIMS` and concentrate on the number of forward citations received within ten years after publication. As is common in the literature (see e.g. Hausman et al., 1984), we use a Poisson regression model approach to take into account the discrete nature of the dependent variable and the large number of zeros. In all other respects, the regression setup follows equation (1).

The results are presented in Table 3, column 3, and mirror the ones from columns 1 and 2. There is a clear positive relation between our aggregated score and the number of citations a patent receives. Once again, results are robust to using unweighted counts of the number of standards associated to a patent.

3.3. Private value of patent protection: renewals

As a last exercise, we look at how patent owners themselves value their patents. In fact, patent holders have to pay maintenance or renewal fees to keep a patent in force.[13] Pakes and Schankerman (1984) and Pakes (1986) have argued that expenses for renewal is an indicator of the private return of holding a patent. The duration of effective patent protection is therefore an indicator of the economic value of a patent, either for the purpose of extracting royalties or to hinder competitors from using the technology.

In the US, renewal decisions are due 3.5, 7.5 and 11.5 years after the grant date and patent holders have to pay a maintenance fee in order to benefit from intellectual property rights. We obtain data on the payment of maintenance fees for USPTO patents for the period 1981–2015 and match these data to our dataset. Patent renewal decisions are a function

[13] After 20 years, patent protection cannot be renewed.

of the age and cohort of the patent and the discounted value of the net economic benefit of holding the patent (see Schankerman, 1998 for a discussion). Empirical analyses therefore turn to survival models where the exit of a patent (i.e. the non-payment of maintenance fees) is described by observable explanatory variables. As is common in the literature, we adopt a Cox hazard model specification (Cox, 1972) to investigate the "survival" of a patent as a function of the sum of scores that a patent "received" between its filing date and the due date of the maintenance fee. Similar to the approach taken in Sections 3.1 and 3.2, we stratify the data by the interaction of the filing year and quarter and the 3-digit IPC class and include 10-year forward citations as a control.

Columns 4 and 5 of Table 3, respectively excluding and including citations as a control, report the beta coefficients of the Cox model. The higher is the score of a patent, the lower is the likelihood that the owner will let that patent expire. In other words, patent holders who observe standardization events that are associated with their patent (over the time window during which the decision has to be taken) are more willing to pay the maintenance fee in order to renew their patent rights. This indicates that our score is positively related to the private value of patents. Results do not change when including grant lags as additional controls or stratifying the data by grant year and quarter.

We therefore conclude that our proximity measure is related to various dimensions of patent quality. However, it is the first that captures a patent's potential for widespread market adoption and/or its utility in deploying new technologies. In this sense, it differs from the measure of patent quality of Kogan et al. (2017), although its construction is similar: firms decided in the past to develop certain technologies/patents and, at the time of the granting of the patent (in our case: at the release of a new standard), additional information about the scientific value of the patent (in our case: its market potential and opportunity of diffusion) become available. In the following section, we will illustrate that standardization offers a distinct value-added that extends beyond the conventional measures of patent quality.

4. The implications of standardization: firm-level results

In this section, we move from patent- to firm-level data. We first relate the firm-level aggregation of patent-to-standard scores, $Tech.Prox_{i,t}$, to financial market data in order to study its information content. In a second step, we relate our proximity measure to real variables to study the implications of standardization in terms of sales, market shares and R&D expenditure.

4.1. Empirical strategy

In order to explain clearly our empirical strategy, it is first important to understand how the standardization procedure works in practice, what is the timing of events from the conception to approval of a standard, and why firms have the incentive to comply with the new standard.

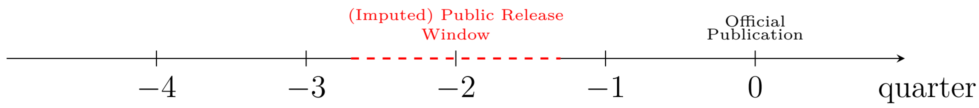
We can briefly summarize the publication path of a standard as follows.[14] Standards

[14] As a reference, see the International Organization for Standardization (ISO) website. Although our

are developed in working groups and technical committees of SSOs. All stakeholders, be they private firms or public sector representatives, can contribute to the standard development – a process that often spans several years. Once the standard is proposed and drafted, it goes under the scrutiny of a committee. This first phase concludes with a vote. If the committee's vote is positive, then the draft of the standard is publicly released and circulated to other sub-committees, external committees of experts, other national or international standard-setting organizations for comments. This corresponds to the very moment that information on the content of the standard becomes available to the public for the first time. In the following phase –which lasts 3 months– suggestions and comments are collected. If no substantial critique is raised, the final version of the draft will be immediately approved and published within the next 6 weeks. On the contrary, if some revision is needed or further analysis is required, then the process is extended in order to give the working group some additional time (2 to 3 months) to comply with the specific requests. Then, the committee has 2 months to judge the revision to the document. If the new draft of the standard is satisfying, then it is approved and published within the following 6 weeks.

As we observe only the official publication date of approved standards, knowledge of the administrative procedure of approval allows to back up for each standard the time window in which the first draft became public knowledge, i.e. roughly between (minimum) 4 and (maximum) 8 months before the final publication date. Figure 1 sketches the timeline (in quarters) of the administrative procedure of standards' approval along with the official publication date in black and the imputed time window of public circulation of the first version of the standard in red. As shown, if publication occurs at time 0, the first (imputed) public release of the standard occurs in a time window around quarter -2.

Figure 1: The Timing of Standards Approval



Notes: This figure sketches the administrative procedure of standards' approval. The official date of publication of the standard by the standard-setting organization is known and occurs at quarter 0. Given information on the administrative procedure of approval and publication of a standard, we back up the (imputed) time window in which the judging committee voted in favor of the standard and made the standard's draft publicly available. This happens roughly around −2, i.e. 2 quarters before the official publication date.

What happens when a standard is finally published? From the moment of the publication onwards, firms are free to chose whether to apply the new standard to their products on a voluntary basis. In fact, standards are not legally binding[15] (unless they are referenced by government regulation, as for example in health or environmental legislation). Yet, it is difficult for an individual firm to not comply with what becomes *standard* in its industry as its products would be at a considerable disadvantage compared to those that follow the standard specifications (Katz and Shapiro, 1994; Farrell and Saloner, 1985).[16] In fact,

dataset does not only include ISO standards, the administrative procedure and the timing of events that leads to the publication of a standard is very similar across SSOs.

[15]They are referred to as *voluntary consensus standards*. See e.g. the general description by ISO.

[16]See Schmidt and Steingress (2022) for the role of harmonized standards for international trade inte-

consumers and producers value products or inputs that are compatible, have a certain quality level or are less subject to information asymmetries. For this purpose, SSOs take on the coordinating role of standard development among industry stakeholders to favor compatibility, interoperability and network effects and to terminate the coexistence of non-compatible alternatives.[17] Therefore, unless a firm is the first to market an entirely new and independent product (see Shapiro and Varian, 1999 for a discussion), non-compliance with a standard can directly harm firms using non-compatible technologies. Therefore, market forces and demand effects can render a standard *de facto* binding, compelling firms to adopt the standardized technology (Katz and Shapiro, 1986) and thereby facilitating convergence towards the new standard.[18]

On the basis of the procedural path of approval and firms' incentives to comply, we can now introduce our empirical model to assess the impact of standardization on firm dynamics. It is important to stress that different standards can be released in subsequent periods. Moreover, differently from a staggered diff-in-diff setup where units are treated only once (e.g. see Callaway and Sant'Anna, 2021), here treatment status can switch multiple times. A firm can be "close" to a standard (i.e. treated) in one period and return to being untreated in the future or sequentially treated at different intensities. Therefore, in order to better isolate the effect of the introduction of a new standard, we resort to a distributed lead-lag model. The main interest of this approach with respect to a static analysis is that it allows to capture the full dynamics of the response. In particular, in our setting, we know that a static model would be biased since the firm's response could be affected also by subsequent and previous releases. Therefore, by controlling for leads and lags of the treatment variable (i.e. $Tech.Prox$), the model captures the dynamic effect of the treatment without assuming that the treatment is permanent. Hence, identification comes from within-firm variation in exposure to standards over time. In light of this, our generic model is described in equation (2):

$$Y_{i,t} = \alpha_i + \phi_{s(i),t} + \sum_{n=-16}^{N=12} \beta_n Tech.Prox_{i,t+n} + X'_{i,t-1}\eta + \varepsilon_{i,t}, \tag{2}$$

where $Y_{i,t}$ is the firm-level dependent variable under consideration. 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.). $Tech.Prox_{i,t}$ expresses the proximity of the stock of patents of firm i to the standard publicly released at t. We include 16 lags and 12 leads of the proximity measure (recall that the time unit here is a quarter). Finally, $X_{i,t-1}$ is a vector of control variables (which we discuss later) and $\varepsilon_{i,t}$ is the error term, which we assume to be normally distributed (conditional on all our covariates) and to be independent across

gration. They argue that the benefits of standardization are a major driver of standard adoption by firms when adoption costs are lowered through the cross-country harmonization of standards, thus increasing trade among countries whose SSOs agree on the same (voluntary) standards.

[17] Early examples of network effects are railway gauges (Gross, 2020), shipping containers (Bernhofen et al., 2016) or the QWERTY keyboard (David, 1985).

[18] We provide evidence on *de facto* compliance and convergence to the standard –occurring only after the release of the standard document– in Section 5, where we discuss the effect of standards on technology spillover and diffusion.

different i.

In this model, β_n measures how the proximity to the standard issued at $t+n$ influences the value of Y measured at t, controlling for the effect of all previous and future standards' releases. We will check that the response of the firm to future releases remains insignificant and will present our results by plotting the values of $\hat{\beta}_n$ for all n, along with its 95% confidence interval. As explained in Schmidheiny and Siegloch (2023), under this set-up, identification of β_n comes from the different within-firm (continuous) exposure to standards across firms over time. Despite of this, in Appendix D.5, we assess the robustness of our results by adapting our dataset to the staggered diff-in-diff framework of Callaway and Sant'Anna (2021). This requires to move from a design with repeated treatments of varying intensity to a design where we only keep the largest $Tech.Prox$ observation per firm and define it as a single binary treatment. The advantage of Callaway and Sant'Anna (2021) is that it provides more robust estimates when treatment is staggered, as it avoids the biases that can arise from comparing newly-treated firms to already-treated ones. Because it requires to binarize the treatment, we will estimate the model restricting to high values (high dose) of $Tech.Prox$ and for low values (low dose) respectively.

4.2. Information effects of standardization

Our goal is to use the proximity measure $Tech.Prox_{i,t}$ to study the effect of standardization on firm-level economic performances and market structure. Before doing so, we want to check the information content of standardization events. We do so for two reasons. First, our proximity measure should pick up a patent's potential for widespread market adoption and/or its utility in deploying new technologies. This differs from dimensions of patent quality already revealed at the time of the patent publication or grant (Kogan et al., 2017). Second, we want to avoid cases of ex-post standardization where the technology selected by the SSO has already been broadly adopted by the time of the standard release.

To do so, we look at how financial markets react when the content of a standard becomes public. If our measure picks up an additional dimension of patent quality that only materializes when a standard is made public, financial markets should update their expectations when new information is disclosed. In the near future following a standard release, firms that already own technologies included in the standard should perform better than their peers as they can immediately deploy and scale their know-how in accordance with the new standard. If markets are efficient (e.g. see Eberhart et al., 2004, Daniel et al., 1998, Mitchell and Stafford, 2000), they should pick up this novel information and discount firms' future performance accordingly. On the contrary, if the technology is already fully adopted, market sentiment about firms close to the standard should not change.

In order to test this, we consider our baseline lead-lag model of equation (2) using two alternative dependent variables aimed at capturing markets' reaction:

1. the abnormal return over a NAICS3-industry portfolio, i.e. $ar_{i,t}^{NAICS3}$;
2. the change in the 1-year EPS forecast from professional agencies, i.e. $\Delta\mathbb{E}[EPS_{i,t+4}] =$

$\mathbb{E}[EPS_{i,t+4}|\mathbb{I}_t] - \mathbb{E}[EPS_{i,t+4}|\mathbb{I}_{t-1}]$, where $\mathbb{I}_t$ is the information set available to professional forecasters in that period.[19]

The vector of controls $X_{i,t-1}$ includes age, q-value of investment, leverage and market capitalization of firm i. We consider these variables to take into account respectively for how long a firm has been listed, its growth opportunities, its capital structure and market value. As explained in Chan et al. (1990) and Szewczyk et al. (1996), these characteristics are important for the magnitude of the stock market reaction following abnormal R&D activity or other innovation-related events.

Figure 2(a) plots all estimated β_n (along with 95% confidence intervals) for the dependent variable $ar_{i,t}^{NAICS3}$. Standard errors are clustered at the firm level. The red area indicates the imputed time window of public release of the standard's content, based on knowledge of the procedure of approval. The red-dashed line indicates the official publication period of the standard, as reported by the standard-setting organization.

Until the (imputed) public release of the standard, the estimated coefficients are not significantly different from zero, i.e. there is no common pre-trend across firms. At $t = -2$, the estimated β is positive and significantly different from zero, which indicates that firms whose patents are closer to the standard over-perform on the stock market and exhibit abnormal returns. This proves that, although the process of standardization is endogenous and markets may know which firms have innovated well in their past, they perceive the standardization event as good news for innovators close to the selected technology only at the moment the standard becomes public.

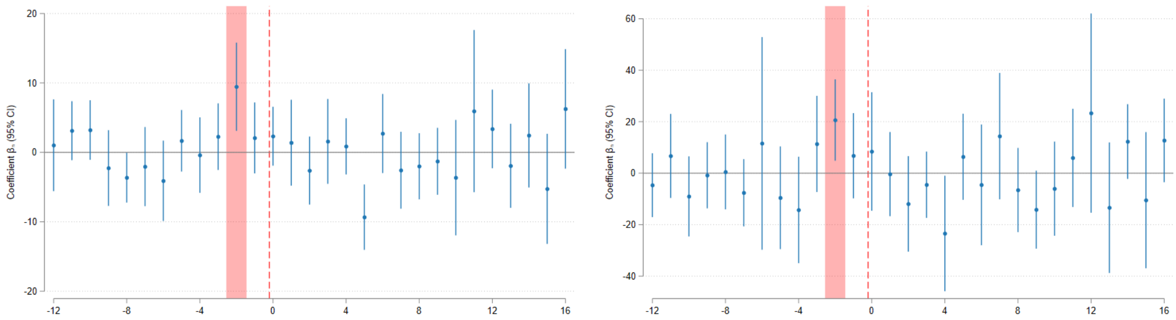
In Figure 2(b), we use the change in the 1-year EPS forecast as dependent variable. Also in this case, we do not observe any pre-trend, but we find that professional forecasters indeed updated their expectations over the future EPS precisely at the time of the public release of the standard. In words, once the information is public, firms whose portfolio of patents is closer to the standard are now expected to have a higher EPS in one year.

In Section 4.5, we test these results (as all others in the following sections) through a large list of robustness checks. Moreover, in Appendix D.1 we show that these results also hold when abnormal returns are extracted with other methodologies (e.g. using the SP500 as measure of market portfolio or through the French-Fama 3-factor model). In Appendix D.2-Appendix D.4, we run a number of robustness checks and show that these results hold when considering our proximity measure at the intensive margin (which demonstrates that proximity to the new standard matters), when using alternative measures of scores for the computation of the proximity measure and another depreciation rate in the aggregation of scores.

The above evidence suggests that the timing of approval of the standard and its specific content represent a surprise for markets beyond what could already be inferred prior to the standard release. In fact, despite knowledge of firms' portfolio of patents, the release of a standard contains additional information that allows markets to re-evaluate firms' future performance. We thus conclude that standardization brings new and non non-negligible

[19]Since the release of a new standard can affect returns and expectations of all firms in the same industry and period, we normalize both dependent variables respectively by the volatility of the NAICS3-industry portfolio and EPS forecast in that period.

Figure 2: Technological Proximity and Financial Markets' Reaction



(a) ar^{NAICS3} (b) $\Delta\mathbb{E}(EPS)$

Notes: Figure 2(a) plots the estimated coefficients of equation (2) (see Section 4.1) when the dependent variable is the firm-level abnormal return computed through the CAPM model with market portfolio defined at the NAICS3 industry-level. Figure 2(b) plots the estimated coefficients when the dependent variable is the change in the 1-year EPS forecast. See Section 2.3 for more information on variables construction. In both figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are clustered at the firm level. The red area indicates the imputed time window of public release of the standard's content, based on knowledge of the procedure of approval. The red-dashed line indicates the official publication of the standard, as reported by the standard-setting organization.

information, and triggers a meaningful economic mechanism: it entails the diffusion and industry-wide adoption of specific technologies, thus enabling firms close to the standard to deploy and scale their know-how faster. Stock markets pick up these effects at the time of information release.

4.3. Implications for sales and market shares

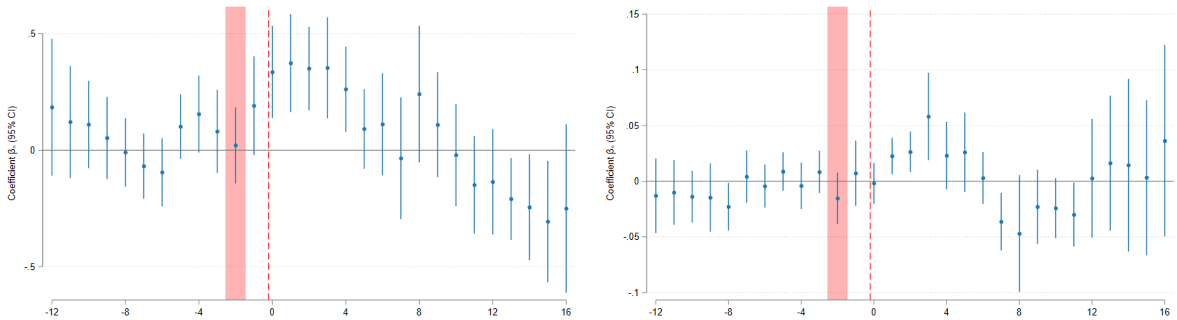
In this section, we investigate whether the release of a standard indeed changes future cash-flows as expected by financial markets. In particular, we study what are the real effects of standardization on sales and market shares.

To do so, we reconsider our baseline lead-lag model of equation (2), but with the normalized value of sales as dependent variable. As from Figure 3(a), after the official date of publication of the standard, firms with a portfolio of patents closer to the new technology standard start to sell more. This increase of sales is positive and significantly different from zero (at the 95% level of significance) for five consecutive quarters. In other words, the firm that can easily adapt to the new technology standard generates higher cash-flows through higher sales. Then, after few quarters in which sales contract, the effects vanishes in the long-run.

It is important to understand if the increase in sales is due to an overall expansion of the market following the standard introduction (*demand effect*) or whether proximity to the adopted technology also leads to gains in terms of market shares (*competition effect*). To check this, we reconsider the same model but with the firm-level market share –defined at NAICS3 level– as dependent variable. As shown in Figure 3(b), consistently with the dynamic of sales, firms that are closer to the technology standard experience a significant –but temporary– expansion of their market share. Then, after a couple of quarters of market-share contraction, the effect vanishes in the long run. As shown in Appendix D.2-Appendix D.4, these results hold in light of the same robustness checks that were discussed in Section 4.2, and when adapting our framework to Callaway and Sant'Anna

(2021) when the treatment is large enough (Appendix D.5). As the definition of markets at the NAICS3 industry-level could be too broad, we show in Appendix D.6 that these results hold also when defining markets by using the definition of product-based market competitors from Hoberg and Phillips (2010, 2016).

Figure 3: Technological Proximity, Sales and Market Share



(a) Sales

(b) Market Share

Notes: Figure 3(a) and 3(b) plot the estimated coefficients of equation (2) (see Section 4.1) when the dependent variable is respectively the level of sales (normalized by the mean-level of fixed assets) and the firm-level market share defined at NAICS3 industry-level. See Section 2.3 for more information on variables construction. In both figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are clustered at the firm level. The red area indicates the imputed time window of public release of the standard's content, based on knowledge of the procedure of approval. The red-dashed line indicates the official publication of the standard, as reported by the standard-setting organization.

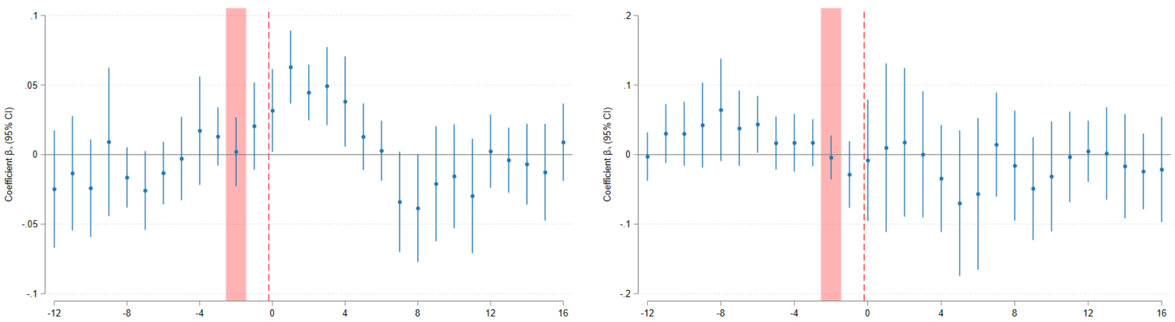
Can we better quantify the effect of standardization? Given how we constructed the proximity measure, it is hard to interpret the estimated coefficients of Figure 4a and 4b in an economically meaningful way. For this reason, instead of the continuous variable $Tech.Prox_{i,t}$, we re-estimate equation (2) with the dummy $\mathbb{I}[Tech.Prox_{i,t} > 0]$ as explanatory variable. We can thus measure the (average) effect of standardization on sales and market shares (now both in logs) for firms close to the standard vis-à-vis firms not affected by standardization at all. By considering the largest estimate of β_n for periods after the standardization event, we find that the maximum (significant) increase in sales and market shares for firms close to the standard is roughly 2.0% for both variables. As this back-of-the-envelope calculation is conducted by considering only the extensive margin of our proximity measure, this estimated impact represents a lower bound.

To conclude, the above evidence suggests that the publication of a standard attributes a competitive advantage to those firms with a portfolio of patents closer to the standardized technology. This advantage translates into higher sales and higher market shares. For this reason, we claim that standardization operates in the market as a (negative) temporary shift in competition.

4.4. Implications for R&D expenditure

If standardization leads to higher sales and market shares, it may also affect firm-level incentives to innovate in the future. However, the incentives to do so should depend on competition. Indeed, if firms are operating in a competitive market, then the short-run advantage that standardization gives to firms close to the standard is very large relative to others. Consequently, given a highly competitive market structure, these firms will strive to keep the lead in the future by investing more into R&D. On the contrary, if the level of competition is too low, i.e. if leading firms were already far ahead of others, then the introduction of a new standard gives lower incentives to innovate as the non-competitive market structure will protect them from future competition. Consistently with the theoretical literature on Schumpeterian growth and competition (Aghion et al., 1997, 2005), we look in this section at whether we observe heterogeneous investment responses to standardization depending on the degree of competition in different sectors.

Figure 4: Technological Proximity and R&D



(a) R&D (Competitive Ind) (b) R&D (Non-Competitive Ind)

Notes: Figure 4(a) and 4(b) plot the estimated coefficients of equation (2) (see Section 4.1) when the dependent variable is the 4-quarter moving average of R&D expenditure (normalized by the mean-level of fixed assets) and the sample is composed respectively by firms operating in a competitive and non-competitive industry. See Section 2.3 for more information on variables construction. In all figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are clustered at the firm level. The red area indicates the imputed time window of public release of the standard's content, based on knowledge of the procedure of approval. The red-dashed line indicates the official publication of the standard, as reported by the standard-setting organization.

To investigate this, first we split industries in those that historically have a markup dispersion above the 75^{th} percentile (non-competitive industries) and those below (competitive industries).[20] We then use our lead-lag model to study the impact of technological proximity on R&D expenditure in competitive and non-competitive industries. If standardization decreases competition, we should find asymmetric results across the two groups of industries.

As shown in Figure 4(a), firms operating in a competitive industry and closer to the technology standard invest more in R&D following a standardization event. This effect starts in the same quarter of the official publication of the standard and lasts five quarters. Conversely, when considering non-competitive industries, as in Figure 4(b), we do not find any significant effect, although point estimates suggest that R&D expenditure is reduced.[21] As shown in Appendix D.2-Appendix D.3, these results hold to the same robustness checks previously listed, and when adapting our framework to Callaway and Sant'Anna, 2021 (Appendix D.5). Finally, in Appendix D.7, we show that these results hold true also when using the Herfindahl-Hirschman Index (HHI) to define competitive and non-competitive sectors.

[20]See data description in Section 2.3

[21]In Appendix D.8, we show that the same dynamics are observed when considering capital investment (CapX) as dependent variable.

All in all, these asymmetric responses corroborate the idea that the introduction of a new standard leads to a temporary (negative) shift in competition that gives a competitive advantage to firms with high proximity values. Since their portfolio of patents better complies with the new standard definition, they are able to expand their market share and –if the market is competitive– they invest more in R&D in order to reinforce and protect their position from future competition.

Yet, it is important to mention that the increase in R&D is the dominating effect when we consider all firms in the sample. In order to quantify the effect of standardization on these variables, we repeat the same analysis as at the end of Section 4.3, i.e. we compare firms close to the technology standard to firms not directly affected by standardization. In this case, we find that the largest effect for the former is an increase in R&D expenditure by 4.8%. As this back-of-the-envelope calculation is conducted by considering only the extensive margin of our proximity measure, this estimated impact represents a lower bound.

4.5. Validation of the proximity measure

In this section, we want to provide evidence that the above results are not driven by confounding factors that affect our proximity measure. Notably, we want to make sure that i) our results are not driven by firms with direct influence on SSOs and the standard development process or by the most innovating firms in the industry, ii) that our proximity measure is not merely capturing the extensive margin of past innovation activity (i.e. the size of the portfolio), strategic patenting activity or the technological field where the firm is operating. By doing so, we will demonstrate that our results are actually driven by the quality and proximity of firms' innovations relative to the new technology standard.

4.5.1. Lobbying SSOs and strategic patenting activity

Our identification relies on the fact that, conditional on all observables, firms are similar except for the nature of their patent portfolio. While our models control for a sector fixed effect and firm characteristics, there might be some unobserved features or strategic behavior that explain why a firm's patents receive a higher score than others. Here, we address this issue from different angles.

Participation in the standard development process. Firms join SSOs as members for two main reasons. First, firms participate in SSOs to acquire information on the standard development process. This can guide their R&D decisions, potentially equipping them with the know-how needed to adapt to future standard releases. To the extent that knowledge about SSOs' activities is public and participation in SSOs is open to all stakeholders, a level playing field is provided such that our proximity measure should correctly pick up firms' innovative capacity. However, this might not always be the case if participation represents a fixed cost that not all industry participants are able to pay (Fiedler et al., 2023). Therefore, our measure could potentially be plagued by differential access to private information produced in SSOs.[22] The second reason for participation is that firms own technologies that can be potentially included in the new standard. If their technologies are selected for their quality, our measure should correctly capture the innovative capacity of these firms. On the other hand, it would be biased if the same firms exercise lobbying and undue influence in order to include their patents into the new standard (see Hall and Ziedonis, 2001; Choi and Gerlach, 2017 and Kang and Bekkers, 2015). This notwithstanding, we want to stress that the role of SSOs is to ensure that the new standard reflects the current consensus in the industry and not the influence of a few players.[23]

While it is impossible to distinguish standards that were subject to undue influence versus those that effectively chose the best available technology, we are able to show that our results hold when controlling for SSO membership using data from Baron and Pohlmann (2018). This database, starting in 1996, reports the name and year of membership of firms when belonging to a SSO. Then, we match this list of firms to Compustat using their names and years of membership and keep only observations from 1996 onwards. We end up with a sample in which 29% of firms were members of a SSO for at least one year,[24] and therefore potentially able to influence the standardization process in their favour around that period. To check whether this is the case, we include a membership dummy in the lead-lag operator of equation (2). This dummy takes value one if the firm is a SSO member in the same year of the standard release or the previous two.[25] This allows us to check if the results of Sections 4.2–4.4 hold or are due to membership around the standardization event. As shown in Appendix E.1, the results are very similar when this additional control is included. In addition, the coefficients of the membership dummy are not significantly different from zero.

To further corroborate this point, we tackle the problem of lobbying in an alternative way. SSOs can be organized on the national level (i.e. US-based such as ANSI, the American National Standards Institute) or on the supranational or international level (i.e. European SSOs such as CENELEC, the European Committee for Electrotechnical Standardization, or ISO, the International Organisation for Standardization). We suppose that US firms have more lobbying power within American SSOs, whereas less so within international ones. In light of this, we go back to our patent-level data and re-build the variable $Tech.Prox_{i,t}$ considering scores obtained from matching patents only to standards issued by international SSOs (which represent 85% of all standards in our data). As shown in Appendix E.2, the results from the previous sections still hold: it is the release of a standard from an international SSO –where US firms have smaller lobbying influence–

[22]If firms are *ex ante* excluded from observing and possibly contributing to the standard development process, our measure would also pick up the lack of a level playing field across firms. As we only analyze publicly listed firms, we are confident that this issue is only a minor one, and can in any case be addressed by firm fixed effects as well as by controlling for SSO membership. Also note that many small firms participate in SSOs (Waguespack and Fleming, 2009; Gupta, 2017).

[23]Spulber (2019) shows in a theoretical model that the voting process in SSOs assures that standards are defined efficiently, as a sufficiently large number of industry participants share its economic benefits. This outweighs the detrimental impact of conveying too much market power to firms that might profit from the chosen standard.

[24]The average membership duration in the data is 2.5 years.

[25]See Appendix E.1 for details.

and the firm-proximity to this standard that explains the results.[26]

Strategic patenting activity. Firms can possibly exploit private information, obtained through their participation in SSOs, and strategically release new patents that are close to the new standard in periods just before its publication. In order to check if our results are not driven by strategic patenting activity, we include the number of patents filed during the year prior to the standardization event in the lead-lag operator of equation (2).[27] This additional control will capture changes in the dependent variable that could result from a more intensive innovation activity in periods just before the release of the standard. As discussed in Appendix E.3, our results are robust to the addition of such a control,[28] i.e. they are not driven by strategic patenting behavior.

Finally, besides lobbying and strategic behavior, some firms might always be more innovative and successful than others due to some unobserved characteristics such as the quality of their management or their innovation culture. Although these (supposedly) time-invariant characteristics are captured by the firm-level fixed effect in equation (2), we show in Appendix E.4 that the results also hold when removing the top 25% of most innovative firms (i.e. those firms that always have larger and more frequent values of $Tech.Prox$).

4.5.2. Measurement issues

In this section, we address several concerns regarding the interpretation of what our $Tech.Prox_{i,t}$ variable is actually capturing. By definition, large values of $Tech.Prox_{i,t}$ may result from a firm owning a large number of patents (extensive margin) and/or from patents that are particularly close to the current technology frontier (intensive margin). While our objective is to capture both dimensions, we want to ensure that our results are not solely driven by the extensive margin. To address this concern, we conduct three tests: (1) a decomposition of $Tech.Prox_{i,t}$ into its extensive and intensive components; (2) a redefinition of $Tech.Prox_{i,t}$ that includes only the best matches; and (3) a placebo exercise in which we randomize the intensive margin. Another concern we seek to address is that $Tech.Prox_{i,t}$ may be disproportionately influenced by a specific technology field in which the firm holds its patents. To this end, we control for the patent portfolio similarity of firms. Lastly, we aim to rule out the possibility that $Tech.Prox_{i,t}$ is driven by firm-specific characteristics or pre-existing trends. To that end, we examine whether firms whose patent portfolios are closer to the technology frontier differ systematically in their characteristics from those that are not.

[26]On the other hand, when considering only standards issued by US SSOs to build the firm-level proximity measure, the effects of standardization on each dependent variable is null or a pre-trend can be detected.

[27]Recall that the variable $Tech.Prox_{i,t}$ is built by aggregating individual scores for all patents filed up to t, where t is the quarter in which the standard is published. Therefore, in the robustness check described in this section, we control for the number of new patents issued between $t-4$ and t. See Appendix E.3 for details.

[28]Results also hold when controlling for the total number of patents accumulated up to one year before the standardization event.

Tech.Prox and patent portfolio size. First of all, we reconsider the definition of the variable $Tech.Prox_{i,t}$, which sums all (depreciated) proximity scores from patents in the portfolio of firm i to every (potentially multiple) standards issued at time t. Being the distribution of scores extremely skewed (see Table 1), i.e. a firm has very few patents that match well a new standard while the majority do not, this definition allows to give more weights to the most important matches generated from the few important patents in the portfolio.[29] On the other hand, it naturally raises the concern that $Tech.Prox$ may largely reflect the extensive margin of innovation: the more patents a firm files and the larger is the portfolio of patents, the higher the chance that some will match a standard, thus inflating $Tech.Prox$ mechanically. To determine whether the sheer volume of patents held by a firm is the primary driver of the results, we decompose the logarithm of $Tech.Prox$ in its extensive margin, directly related to the size of the portfolio, and intensive/quality margin, which reflect the average proximity of matched patents to a new standard, the average coverage of a matched patent over multiple standards, and the probability of having a patent in the portfolio matching a standard. In Appendix E.5, we regress separately each component on the logarithm of $Tech.Prox$, and assess its contribution via the R-squared. The size of the portfolio explains up to 40% but, once controlling for firm and industry-time fixed-effects, it explains only 5% of the total variation of $Tech.Prox$. The remainder is explained by the intensive/quality margin. Hence, we conclude that our matching algorithm and our proximity measure effectively captures variation in the quality of innovation, not just its quantity.

As a second test, we redefine the proximity measure using only the highest-quality matches in order to validate that most patent-to-standard scores are near zero and thus that only a few high-quality patents drive our result. For each standard and IPC category, we identify the three patents with the highest cosine similarity scores and compute the average similarity across these top matches. We then construct the firm-level $Tech.Prox$ variable accordingly and estimate the led-lag model of Section 4.1. As shown in Appendix E.6, using this restricted definition, the main results continue to hold.

Finally, to further corroborate that it is the quality of innovation (the intensive margin) that matters, we conduct a placebo exercise in Appendix E.7. In particular, for each patent and standard, we re-assign standard proximity scores randomly, and repeat this process 1000 times. In each iteration, we aggregate placebo scores at the firm level to construct the (placebo) variable $Tech.Prox$ and re-estimate the lead-lag model. If the results were solely driven by the size of a firm's patent portfolio, we would expect the dynamics of outcomes to mirror those observed in the baseline estimates. However, the placebo results are flat and statistically insignificant across all outcomes (see Figure E.7 in Appendix E.7). Moreover, we show that the true estimates statistically differ from the placebo ones (see Figure E.8). Overall, this evidence indicates that merely holding a large patent portfolio is not sufficient. What proves critical is the quality and specificity of the match between a firm's patents and the relevant standard. Our measure is capturing this substantive dimension.

[29] Conversely, averaging the scores across all patents in the portfolio would mute the explanatory power of the variable $Tech.Prox$ as the scores from the few good matches will be inevitably diluted.

Portfolio similarity. We want to exclude the possibility that specific technological fields in which firms innovate, or combinations thereof, are driving our results. To do so, we construct a network of firms based on the co-occurrence of the IPC classes of their patents. We then use a k-mean clustering algorithm to construct 100 groups of firms. Within these groups, firms are therefore similar in terms of the technological classes of their patents. We then augment our lead-lag model by adding a dummy for each of these groups interacted with a time fixed effect. If our results hold, then this would corroborate that even within firms that patent in similar technologies, those that are closer to a new standard increase their sales, market share and R&D. Results and details are presented in Appendix E.8 which shows that our baseline findings are indeed robust to this test. Note that this also ensures that our matching procedure captures more than just the nature of the technology and is able to differentiate between patents of similar technologies.

Firm homogeneity. A final concern we address is that $Tech.Prox_{i,t}$ may be correlated with other observable firm characteristics, raising the possibility that our regression results reflect these factors rather than a firm's innovative history that determines its current proximity to the technology frontier. In Appendix E.9, we show that, conditional on firm fixed effects, firms with a positive value for the proximity measure ($\mathbb{I}[Tech.Prox > 0]$) do not significantly differ ex-ante[30] from others in several dimensions such as: q-value of investment, leverage, market capitalization, return on equity (ROE), price/earning ratio, cost of capital, size, age. Table E.2 (columns 9 and 10) also mirrors the results from above on the small contribution of the extensive margin: the number of newly issued patents or the cumulative number of patents do not explain the proximity measure. This corroborates the idea that strategic patenting and the patent portfolio size do not guarantee that firms are close to the technological frontier.[31]

All in all, this further evidence confirms that our proximity measure is meaningful in terms of measuring the quality of a firm's patent portfolio with respect to the newly standardized technology at the time the new standard document is released.

5. Aggregate effects and implications

The aggregate impact of standardization can be analyzed by considering its short-term and long-term effects separately. As discussed in the previous section, standardization provides an immediate temporary advantage to firms that are close to the technology standard. However, the primary objective of standardization is to foster the diffusion and large-scale adoption of industry best practices. Over the long term, this can have a positive aggregate effect by mitigating information frictions and facilitating technology transfer.

In this section, we test this mechanism of technology diffusion for growth. Our analysis is motivated, among others, by the findings of Bloom et al. (2013): R&D efforts yield

[30]Four quarters before the release of a new standard.

[31]In addition, we checked that, controlling for the number of patents, there is no correlation between the lagged market share and the magnitude of $Tech.Prox$. In other words, market power does not explain why a firm receives a positive value for $Tech.Prox$.

benefits for the innovating firms, but in the long-run, technology spillovers to other firms become the dominant effect. Indeed, as demonstrated in Rysman and Simcoe (2008), the goal of standardization is to enhance and incentivize this diffusion process by creating a shared knowledge base for industry participants to build upon. Therefore, standardization could be a pivotal driver of economic growth, as knowledge diffusion not only allows for catch-up but also encourages new innovation, as suggested by Hegde et al. (2022) and Furman et al. (2021).

In light of this, the aggregate effect of standardization should be viewed as a combination of a short-term effect of increasing the advantage of leaders, and a long-term effect where other firms benefit from technological spillovers and increase their research effort. Which one of these two competing effects on aggregate growth dominates?

To answer this question, we first study if standardization leads to higher growth at industry-level. In particular, we study how much of the change in growth following the release of a new standard can be explained by leaders and by the rest of the industry, i.e. the followers. Second, we analyze the dynamics of followers in response to standardization and show that they catch up in terms of innovation activity and economic performance. This process stimulates sectoral competition and boosts sectoral.

Finally, we provide evidence of knowledge spillovers and (ex-post) convergence towards the standard to explain the catching-up process of followers.

Sectoral growth through standards. Our empirical analysis in Section 4 shows that when a firm is close to the standard ($Tech.Prox_{i,t} > 0$), then it has an immediate competitive advantage compared to its competitor in the same market that translates into higher sales and market share. This positive effect implies that these firms can be, at least temporarily, seen as the leader in their industry as they are now closer to the newly defined technology standard. In light of this, we split the Compustat sample of firms used in the previous sections into two groups. For every industry and quarter, we define as *leaders* those firms with $Tech.Prox_{i,t} > 0$, and *followers* all the others. Then, we aggregate and build an industry-level panel dataset where sectoral sales and their growth rate are decomposed between leaders and followers. As shown in Table 4, the average industry grows by 1.64% per quarter. With a rate of 1.04% (0.60%), leaders (followers) explain 63% (37%) of sectoral growth.

Given these figures, we now study the (cumulative) effect of standardization on sectoral growth, and by how much the change in growth is explained by leaders and followers. For this, we consider again model (2), but now defined for our industry-level panel dataset.[32] We estimate this model with the dependent variable being the industry growth rate as well as the growth rate of leaders and followers. The explanatory variable is the average value of our proximity measure for leaders for each quarter and industry. This captures to which extent the average leader in the industry can adapt to the new standardized

[32] Since we are now dealing with a panel where the dependent variables and covariates are defined at the industry level, we drop the interaction between industry and time fixed effects from model (2) as this would capture all the within-industry variation over time. The set of control variables remains the same as in the firm-level exercise, but they are here aggregated at NAICS3 level. Appendix F explains in detail the construction of the industry-level data and the empirical model used in this section.

Table 4: Aggregate Effects on Growth

	Industry	*Leaders*	*Followers*
Mean Sectoral Growth Rate (%)	1.64	1.04	0.60
(1yr-Cumulative) Change in Growth due to Mean Sectoral Shock (pp)	-0.05 (0.04)	0.05 (0.03)	-0.10 (0.06)
(4yr-Cumulative) Change in Growth due to Mean Sectoral Shock (pp)	0.19 (0.10)	0.01 (0.04)	0.18 (0.07)

Notes: The first line of this table shows the average sectoral growth and its decomposition between leaders and followers. The second and third line show the cumulative effect of the introduction of a standard on sectoral growth respectively one and four year after the official publication of the standard. Standard errors are in parenthesis. See Appendix F for details on data and estimation.

technology at the moment of the release of the standard. We estimate the model and sum the coefficients over the first year and first-to-forth year after the publication of the standard (see Figure F1 in Appendix F). This allows us to quantify the short- and long-run effect of standardization on sectoral growth along with the contribution of followers and leaders.

As reported in the second line of Table 4, in the first year after the introduction of the standard, sectoral growth decreases by 0.05pp for the average value of our sectoral proximity measure. When looking at the decomposition, we find that the growth rate of leaders increases by 0.05pp as they benefit from being close to the new technology standard. This effect is counterbalanced by the negative growth rate of followers. In fact, since followers are by definition far away from the standard, the more leaders in the same industry are mastering the new technology the less followers grow in the short-run. For the average sectoral proximity of leaders, followers' growth rate diminishes by 0.10pp. Over the four years following the introduction of the standard, the contribution among leaders and followers reverses. In fact, in the long-run, the industry starts growing faster. The more leaders were close to the technology standard at the moment of standard release, the more sectoral growth increase (by 0.19pp for the average value of $Tech.Prox$ after four years). This result is mostly explained by followers –for which the growth rate increases (significantly) by 0.18pp– and not by leaders whose contribution is small and insignificant.

Catching-up effects and increasing competition. In line with the evidence from Section 4.3, these results corroborate the idea that the gains for leaders are only temporary. On the other hand, it seems that it is followers that drive sectoral growth in the long-run. If the catching-up motive is in action, we should observe a bigger increase in followers' sales and R&D investment in sectors in which the distance from the technology standard of the (average) leader and follower is larger, i.e. in industries where the introduction of a new standard can potentially generate stronger spillovers. To check this, we use our industry-level panel and relate leaders to followers by constructing the following industry-level variables: (i) the industry-level market share of followers, (ii) the followers' share of total R&D expenditure in the industry, (iii) the followers' share of total patents issued in the industry. Then, we use (i)-to-(iii) as dependent variables for model (2) adapted to sectoral-level data. Hence, by doing so, it is possible to understand which group drives sales and innovation in the industry, by how much and when. Figure 5(a) shows that, in industries where the average leader is closer to the technology standard and the average distance between leaders and followers is larger, followers' aggregate market shares decline at the end of the first year following the introduction of the standard. However, from the end of the third year, this dynamic is reverted as the market share of followers increases persistently for the remaining periods. Figure 5(b) shows that –starting from the third year after the introduction of the standards– followers increase their R&D expenditure relatively to leaders in the industry. This pattern is confirmed by Figure 5(c): sectoral research output is mostly explained by followers in the long-run.[33] Finally, in light of this evidence, we study if the introduction of a new standard also have aggregate implications on sectoral competition. In fact, as followers catch up through higher innovation activity and output, within-industry competition should increase. Here, we investigate this issue by looking at the evolution of the Herfindahl-Hirschman Index (HHI) when frontier firms take a stronger lead by being closer to the new frontier defined by the standard. As shown in Figure 5(d), concentration declines in the long-run following standardization. In Appendix F, we provide further evidence that sectoral markups increase only in the very short-run and due to leaders. Conversely, markup dispersion tends to decrease in the very long-run as followers catch up.

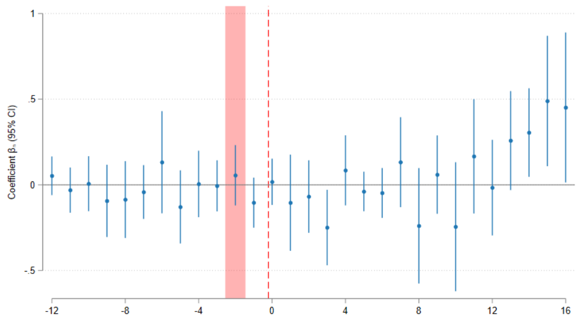
To sum up, in the short-run, the few leaders benefit from their advantage from being in proximity of the new standard. But in the long-run, laggard firms –which represent the majority of firms– benefit from knowledge spillovers, increase their R&D, and are able to catch up –or even surpass– the initial leaders through higher sales. This process fuels sectoral growth and contributes to a more competitive market environment.

Convergence to the standard and knowledge spillovers. To show that the catching-up is indeed driven by spillovers, here we study pre- and post-standardization convergence of firms to the newly standardized technology. This exercise will further clarify the role of SSOs in reducing information frictions as standards give clear indications on the direction of future innovation. In fact, we are able to show that firms react accordingly and converge to the standard only once it is published, and not before. Therefore, this suggests that firms do not clearly know which technology will be standardized and –consequently– that the standardized technology has not yet diffused before the definition of the standard. This supports the idea that SSOs do not merely endorse technologies that are already widespread (ex-post standardization). Furthermore, this evidence also sustains the idea that firms *de facto* comply with new standards although they are not legally binding.

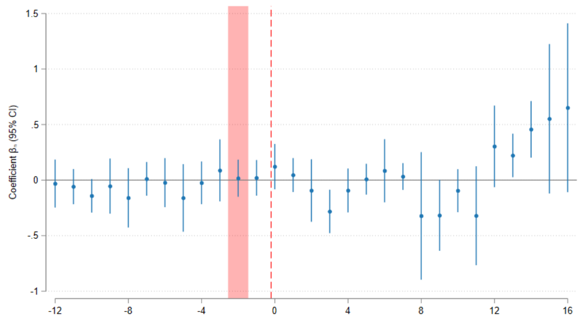
To this end, we use our patent/standard-level data and restrict attention to the subsample of patents that can be matched to Compustat firms. For each standard s published at time τ, we collect all patents matching standard s and issued in a 5-year window before and after τ. Across all such windows, we analyze 60,839 standards. For each standard s, we define $score^{Best}_{t^*<\tau,s}$ as the maximum score, realized at time t^*, among all patents matched to s and issued before τ. By doing so, we define an initial reference point that captures to which extent the best patent, for a given standard, was originally close to the

[33] Using levels as dependent variable does not substantially change the results. We therefore conclude that the results are not driven by composition effects: the increase in followers' shares is not an artifact of leaders' dynamics.

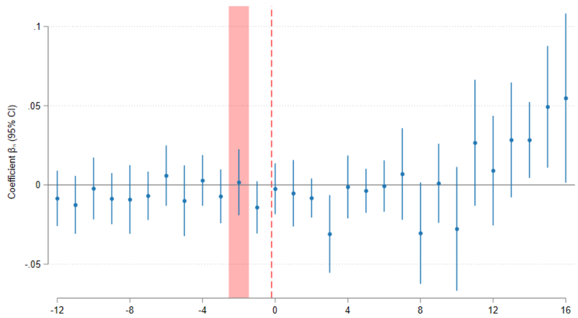
Figure 5: Aggregate Effects of Standardization



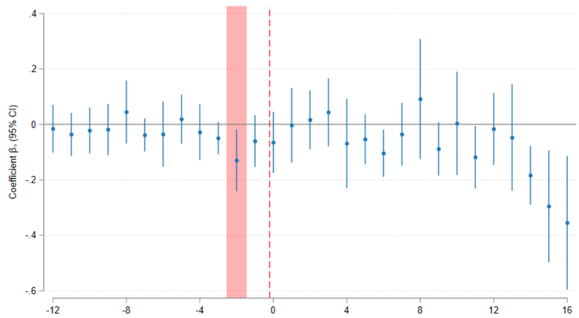
(a) Market Share (Followers)



(b) Share of R&D (Followers)



(c) Share of New Patents (Followers)



(d) *HHI*

Notes: Figures 5(a)-5(d) plot the estimated coefficients when the dependent variable is respectively: the market share of followers in the NAICS3 industry, the followers' share of total R&D expenditure in the NAICS3 industry, the followers' share of total patents issued in the NAICS3 industry, the sectoral (normalized) Herfindahl-Hirschman Index (HHI). See Appendix F for more details on data construction and estimation. In all figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are double-clustered at (NAICS3) industry-level and date. The red area indicates the imputed time window of public release of the standard's content, based on knowledge of the procedure of approval. The red-dashed line indicates the official publication of the standard, as reported by the standard-setting organization.

frontier.[34] Then, we estimate the following model separately for the sample of patents issued before and after the standard:[35]

$$\log\left(\frac{score_{i,j,s}}{score^{Best}_{t^*<\tau,s}}\right) = \alpha + \beta \log(score^{Best}_{t^*<\tau,s}) + \gamma \cdot time_{i,s} + \delta_{t(j)} + \epsilon_{i,j,t} \quad \forall j \in \{t^* < t < \tau;\ t > \tau\}, \tag{3}$$

where $score_{i,j,s}$ denotes the score of patent i (issued at time j) with respect to standard s. $time_{i,s}$ is the number of quarters between the patent and the standard's publication –taken in absolute value depending on whether $t^* < j < \tau$ or $j > \tau$. $\delta_{t(j)}$ is a time fixed effect capturing time-variation common to all patents filed in the same period j.

This model studies to which extent newer patents reach (or surpass) the initial reference point, and therefore whether there is convergence to the standard. If convergence occurs, we should observe $\beta < 0$ which implies that: i) the distance between observed new

[34]On average, the best patent covers 40% of the semantic content of the standard, and the top 5% reach a match of 75%.

[35]We borrow this statistical tool from Barro and Sala-i Martin (1992) to analyze convergence, which is base on a differential equation describing the convergence process of a variable towards a steady state.

scores and the best pre-standard score shrinks over time, ii) the effect is bigger (i.e. the speed of convergence is faster) the larger is the initial gap and therefore the larger is the potential effect of spillovers from leaders to followers triggered by the standard. Hence, the model captures both margins: faster convergence and higher spillovers for standards where patents are initially far away from the frontier.

Estimating this model in periods before and after the release of the standard will unveil if and when the convergence process occurs. When estimating the model for $t^* < j < \tau$ (columns 1 and 2 of Table 5), we find an insignificant β whether we control for $time_{i,s}$ or not . This indicates that –despite the quality of the best patent being observable– newer patents are not better. In other words, there is no converge on a common technology. This corroborates the idea that firms do not know yet which technologies will be codified in the forthcoming standard prior to its release, and that the diffusion of the standardized technology does not occur before publication. By contrast, when considering patents issued after the release (columns 3 and 4), we now find $\beta < 0$, implying that newer patents are improving fast and resembling more the new standard. This pattern reflects post-publication convergence, consistent with our interpretation of standards as coordination mechanisms that shape the subsequent direction of technological development and stimulate diffusion of the best technologies.[36]

Next, we examine whether this convergence is driven by firms that were already partially aligned with the future standard ("frontier" firms) or by firms that were initially far. We define a dummy $\mathbb{I}(Frontier\ Firm_i)$ equal to 1 if patent i belongs to a firm that had at least one patent with a positive score prior to the release of the standard, and 0 otherwise. Column 5 includes this dummy and finds a stronger convergence effect. Column 6 adds an interaction term $\log(score^{Best}_{t^*<\tau,s}) \times \mathbb{I}(Frontier\ Firm_i)$ to test whether convergence differs by firm type. The results show that non-frontier firms (initially far from the standard) experience faster convergence with a rate of 22%. Frontier firms –already close to the standard– adjust less, with a convergence rate around 7%. This pattern reinforces our firm- and sector-level findings: standardization facilitates diffusion of best practices, promotes convergence from laggard firms, and contributes to sectoral growth. In Appendix G.2, we provide further evidence of this mechanism. Using the same data, we show that –within every sub-group of patents matching a standard– scores from patents filed prior to the publication of the standard are stable whereas they increase starting from the publication of the standard onwards. This effect is mostly explained by followers, i.e. firms that did not have any patent originally close to the standard. This indeed confirms that disclosure of the standard releases new information that is taken into account by firms when producing new patents. In Appendix G.3, we show that also the quantity of new patents increases, i.e. standardization triggers more innovation at the extensive margin.

As final evidence, we study the evolution of citations of the patents of a firm received from other firms. To do so, we use the network of citations from our patent data and the patent-to-firm crosswalk from Kogan et al. (2017), such that we can pin down the number

[36] In Appendix G.1, we conduct a placebo exercise demonstrating that the result on convergence is not driven by noise in the data. In fact, as our scores could potentially capture some noise due to random matches, convergence could be an artifact of the data generating process due to mean reversion. We show that this is not the case in our data.

Table 5: Convergence towards the new standard

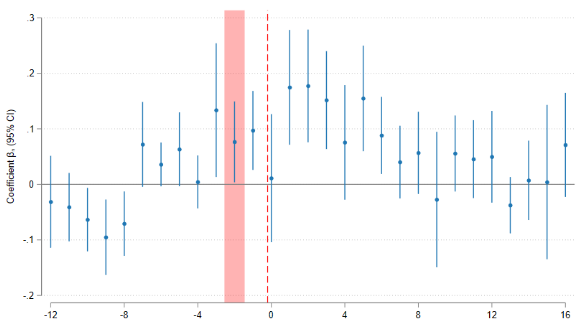
	(1)	(2)	(3)	(4)	(5)	(6)
	Pre-standard Release		*Post-standard Release*			
$log(score^{Best}_{t^*<\tau,s})$	-0.0018	0.0136	-0.0895***	-0.0892***	-0.1897***	-0.2209***
	(0.0091)	(0.0093)	(0.0096)	(0.0096)	(0.0080)	(0.0089)
$log(score^{Best}_{t^*<\tau,s}) \times \mathbb{I}(Frontier\ Firm)$						0.1501***
						(0.0130)
Observations	334,610	334,610	383,338	383,338	383,338	383,338
Patent filing date Fe	Yes	Yes	Yes	Yes	Yes	Yes
N. of qtr to/from Standard Pub.	No	Yes	No	Yes	Yes	Yes
Frontier Firm	–	–	No	No	Yes	Yes

Notes: Patent-level regressions. The dependent variable is the logarithm of the ratio between the variable $score_{i,s}$ and $score^{Best}_s$ which respectively represent the score obtained from matching i with standard s, $score^{Best}_s$ whereas is the highest score realized by the best patent in the 5 years prior to the publication of standard s. *time* is the number of quarters intercurrent before or after the publication of the standard. $\mathbb{I}(Frontier\ Firm_i)$ indicates whether patent i belongs to a firm that was already close to the standard prior to its publication. "*", "**" and "***" designate significance at the 1%, 5% and 10% level.

of (contemporaneous) citations a patent receives from either a laggard or a leader. Then, we aggregate the number of citations at the firm level and re-run model (2) with the share of citations from followers. Figure 6 shows that firms whose portfolio of patents match well the new standards are cited more by laggard firms.

In light of this, consistently with the theoretical literature (Aghion et al., 2005, Acemoglu et al., 2012 and Perla and Tonetti, 2014), we conclude that the definition of a technology standard incentivizes firms far away from the standard to adopt the new technology and further innovate in order to catch up. Therefore, we conclude that standardization acts as a trigger: initially reinforcing existing advantages to leaders, but ultimately promoting diffusion, convergence, further innovation and increased competition from laggards. This mechanism, contributes to economic growth.

Figure 6: Patent Citations from Followers



Notes: Figure 6 plots the estimated coefficients of equation (2) when the dependent variable is the share of the number of patent citations leaders receive from laggard firms. The 95% confidence intervals for each point-estimate is reported. Standard errors are clustered at the firm level. The red area indicates the imputed time window of public release of the standard's content, based on knowledge of the procedure of approval. The red-dashed line indicates the official publication of the standard, as reported by the standard-setting organization.

6. Conclusion

This paper studies how standardization –i.e. the selection and adoption of a new technology at the industry level– affects competition, innovation and growth at the firm and sectoral level. The contribution of the paper is threefold.

First, we use semantic algorithms to match the content of patents and standards. This methodology allows to measure the proximity of each patent to the new technology standard, and –therefore– the capacity of firms to market their products accordingly. We show that the information retrieved from the semantic matching is meaningful as patents closer to the content of a standard are associated with greater economic, scientific and private value.

Second, we cross this novel measure with firm-level data to study (i) to which extent standardization is distinct from just observing patent quality, and (ii) how firm dynamics change depending on the proximity of the firm's portfolio of patents to the new standard.

We address these questions through a dispersed lead-lag model, which captures the entire response following the release of a new standard. Under this strategy, we show that financial markets do not anticipate the timing and content of a standard. In fact, markets react only at the very moment that information on the new standard becomes public. Thereafter, we show that firms closer to the new standard gain temporarily in terms of sales and market shares once the standard is published. This suggests that standardization affects market structure since it gives a temporary competitive advantage to those firms that have the technology and knowledge to immediately adjust to the standard specifications. In addition, we also observe heterogeneous reactions across markets. In markets with high levels of competition, firms closer to the new technology standard do more R&D after the release of the standard.

In the final part of the paper, we investigate the aggregate implications of standardization at the industry level. We find that sectors in which the potential for knowledge spillovers is higher exhibit higher growth in the long-run. This is only partially explained by the gains of the leaders in the industry. Actually, sectoral long-term growth is mostly explained by followers. In fact, in those industries, followers invest more in R&D and their research output is higher. This allows them to catch up and the industry to grow more and to become more competitive in the long-run.

In light of these results, this paper not only sheds light on the effect of standardization on competition and innovation, but it shows that standardization rewards firms whose portfolio of patents aligns well with the new technology standard while, at the same time, stimulating further investment by followers and –ultimately– economic growth. However, this result should not be interpreted as a statement about the optimality of the standard-setting process nor does it exclude heterogeneous effects across different types of standards. Yet, this paper highlights the importance of microeconomic mechanisms of technology adoption, usually discussed in the IO literature on SSOs, for the macroeconomy. Therefore, it calls for a deeper integration of IO theory into macroeconomic models in order to foster our understanding of standards and their implications for welfare, technological spillovers, or efficiency.

References

Abbas, A., Zhang, L., Khan, S.U., 2014. A literature review on the state-of-the-art in patent analysis. World Patent Information 37, 3–13. URL: https://www.

sciencedirect.com/science/article/pii/S0172219013001634, doi:https://doi.org/10.1016/j.wpi.2013.12.006.

Acemoglu, D., Gancia, G., Zilibotti, F., 2012. Competing engines of growth: Innovation and standardization. Journal of Economic Theory 147, 570–601.

Aghion, P., Bergeaud, A., Lequien, M., Melitz, M., Zuber, T., 2021. Opposing firm-level responses to the China shock: horizontal competition versus vertical relationships? Technical Report w29196. National Bureau of Economic Research.

Aghion, P., Bergeaud, A., Lequien, M., Melitz, M.J., 2018. The heterogeneous impact of market size on innovation: evidence from French firm-level exports. Technical Report w24600. National Bureau of Economic Research.

Aghion, P., Bloom, N., Blundell, R., Griffith, R., Howitt, P., 2005. Competition and innovation: an inverted-u relationship. The Quarterly Journal of Economics 120, 701–728. URL: http://qje.oxfordjournals.org/cgi/doi/10.1093/qje/120.2.701, doi:10.1093/qje/120.2.701.

Aghion, P., Griffith, R., 2005. Competition and growth: reconciling theory and evidence. MIT press.

Aghion, P., Harris, C., Vickers, J., 1997. Competition and growth with step-by-step innovation: An example. European Economic Review 41, 771–782.

Aghion, P., Howitt, P., 1992. A Model of Growth through Creative Destruction. Econometrica 60, 323–351.

Akcigit, U., Ates, S.T., Impullitti, G., 2018. Innovation and trade policy in a globalized world. Technical Report w24543. National Bureau of Economic Research.

Argente, D., Baslandze, S., Hanley, D., Moreira, S., 2020. Patents to products: Product innovation and firm dynamics. FRB Atlanta Working Paper 2020-4. Federal Reserve Bank of Atlanta. URL: https://ideas.repec.org/p/fip/fedawp/87832.html.

Arts, S., Cassiman, B., Gomez, J.C., 2018. Text matching to measure patent similarity. Strategic Management Journal 39, 62–84. URL: https://onlinelibrary.wiley.com/doi/abs/10.1002/smj.2699, doi:https://doi.org/10.1002/smj.2699, arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1002/smj.2699.

Austin, D.H., 1993. An event-study approach to measuring innovative output: The case of biotechnology. The American economic review 83, 253–258.

Autor, D., Dorn, D., Hanson, G., Pisano, G., Shu, P., 2020. Foreign competition and domestic innovation: Evidence from us patents. American Economic Review: Insights 2, 357–74.

Baron, J., Pohlmann, T.C., 2018. Mapping standards to patents using declarations of standard-essential patents. Journal of Economics and Management Strategy forthcoming.

Baron, J., Schmidt, J., 2014. Technological Standardization, Endogenous Productivity and Transitory Dynamics. Working papers 503. Banque de France.

Baron, J., Spulber, D.F., 2018. Technology standards and standard setting organizations: Introduction to the searle center database. Journal of Economics & Management Strategy 27, 462–503. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/jems.12257, doi:10.1111/jems.12257, arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1111/jems.12257.

Barro, R.J., Sala-i Martin, X., 1992. Convergence. Journal of political Economy 100, 223–251.

Basu, S., Fernald, J.G., 2008. Information and communications technology as a general purpose technology: Evidence from u.s. industry data. Federal Reserve Bank of San Francisco Economic Review , 1–15.

Bekkers, R., Bongard, R., Nuvolari, A., 2011. An empirical study on the determinants of essential patent claims in compatibility standards. Research Policy 40, 1001–1015. Issue dedicated to Chris Freeman, Founding Editor.

Bekkers, R., Catalini, C., Martinelli, A., Righi, C., Simcoe, T., 2017. Disclosure Rules and Declared Essential Patents. Working Paper 23627. National Bureau of Economic Research. URL: http://www.nber.org/papers/w23627, doi:10.3386/w23627.

Benhabib, J., Perla, J., Tonetti, C., 2021. Reconciling models of diffusion and innovation: A theory of the productivity distribution and technology frontier. Econometrica 89, 2261–2301.

Bergeaud, A., Potiron, Y., Raimbault, J., 2017. Classifying patents based on their semantic content. PloS one 12, e0176310.

Bergeaud, A., Schmidt, J., Zago, R., 2022. The implications of technological standardization for the value of the firm. mimeo .

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

Bernhofen, D.M., El-Sahli, Z., Kneller, R., 2016. Estimating the effects of the container revolution on world trade. Journal of International Economics 98, 36–50. URL: https://ideas.repec.org/a/eee/inecon/v98y2016icp36-50.html, doi:10.1016/j.jinteco.2015.09.

Bloom, N., Draca, M., Van Reenen, J., 2016. Trade induced technical change? the impact of chinese imports on innovation, IT and productivity. The Review of Economic Studies 83, 87–117. URL: http://restud.oxfordjournals.org/lookup/doi/10.1093/restud/rdv039, doi:10.1093/restud/rdv039.

Bloom, N., Hassan, T.A., Kalyani, A., Lerner, J., Tahoun, A., 2021. The Diffusion of Disruptive Technologies. Working Paper 28999. National Bureau of Economic Research. URL: http://www.nber.org/papers/w28999, doi:10.3386/w28999.

Bloom, N., Schankerman, M., Van Reenen, J., 2013. Identifying technology spillovers and product market rivalry. Econometrica 81, 1347–1393. URL: http://dx.doi.org/10.3982/ECTA9466, doi:10.3982/ECTA9466.

Brachtendorf, L., Gaessler, F., Harhoff, D., 2020. Approximating the standard essentiality of patents – A semantics-based analysis. Technical Report. Report for the EPO Academic Research Programme.

Brachtendorf, L., Gaessler, F., Harhoff, D., 2022. Truly standard-essential patents? a semantics-based analysis. Journal of Economics & Management Strategy forthcoming, 1–26. doi:https://doi.org/10.1111/jems.12500.

Brown, J.R., Fazzari, S.M., Petersen, B.C., 2009. Financing innovation and growth: Cash flow, external equity, and the 1990s r&d boom. The Journal of Finance 64, 151–185.

Callaway, B., Sant'Anna, P.H., 2021. Difference-in-differences with multiple time periods. Journal of Econometrics 225, 200–230.

Chan, S.H., Martin, J.D., Kensinger, J.W., 1990. Corporate research and development expenditures and share value. Journal of Financial Economics 26, 255–276.

Choi, J.P., Gerlach, H., 2017. A theory of patent portfolios. American Economic Journal: Microeconomics 9, 315–51. URL: https://www.aeaweb.org/articles?id=10.1257/mic.20150003, doi:10.1257/mic.20150003.

Cox, D.R., 1972. Regression models and life-tables. Journal of the Royal Statistical Society: Series B (Methodological) 34, 187–202.

Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor psychology and security market under-and overreactions. the Journal of Finance 53, 1839–1885.

David, P.A., 1985. Clio and the economics of qwerty. American Economic Review 75, 332–337.

De Loecker, J., Eeckhout, J., Unger, G., 2020. The rise of market power and the macroeconomic implications. The Quarterly Journal of Economics 135, 561–644.

Dechezleprêtre, A., Hémous, D., Olsen, M., Zanella, C., 2021. Induced automation: evidence from firm-level patent data. Technical Report 384. University of Zurich, Department of Economics.

Eberhart, A.C., Maxwell, W.F., Siddique, A.R., 2004. An examination of long-term abnormal stock returns and operating performance following r&d increases. The Journal of Finance 59, 623–650.

Edmond, C., Midrigan, V., Xu, D.Y., 2015. Competition, markups, and the gains from international trade. American Economic Review 105, 3183–3221.

Farrell, J., Klemperer, P., 2007. Coordination and lock-in: Competition with switching costs and network effects, in: Armstrong, M., Porter, R. (Eds.), Handbook of Industrial Organization. Elsevier. volume 3. chapter 31, pp. 1967–2072.

Farrell, J., Saloner, G., 1985. Standardization, Compatibility, and Innovation. RAND Journal of Economics 16, 70–83.

Farrell, J., Saloner, G., 1986. Installed base and compatibility: Innovation, product preannouncements, and predation. American Economic Review 76, 940–955.

Farrell, J., Simcoe, T., 2012. Choosing the rules for consensus standardization. The RAND Journal of Economics 43, 235–252.

Fiedler, C., Larrain, M., Prüfer, J., 2023. Membership, governance, and lobbying in standard-setting organizations. Research Policy 52, 104761.

Furman, J.L., Nagler, M., Watzinger, M., 2021. Disclosure and subsequent innovation: Evidence from the patent depository library program. American Economic Journal: Economic Policy 13, 239–70.

Griliches, Z., 1990. Patent Statistics as Economic Indicators: A Survey. Journal of Economic Literature 28, 1661–1707.

Gross, D.P., 2020. Collusive investments in technological compatibility: Lessons from u.s. railroads in the late 19th century. Management Science 66, 5683–5700. doi:10.1287/mnsc.2019.3504.

Grossman, G.M., Helpman, E., 1991. Quality ladders in the theory of growth. The Review of Economic Studies 58, 43. URL: http://restud.oxfordjournals.org/lookup/doi/10.2307/2298044, doi:10.2307/2298044.

Gupta, K., 2017. How ssos work: Unpacking the mobile industry's 3gpp standards.

Hall, B.H., Jaffe, A., Trajtenberg, M., 2005. Market Value and Patent Citations. RAND Journal of Economics 36, 16–38.

Hall, B.H., Ziedonis, R.H., 2001. The Patent Paradox Revisited: An Empirical Study of Patenting in the U.S. Semiconductor Industry, 1979-1995. RAND Journal of Economics 32, 101–128. URL: https://ideas.repec.org/a/rje/randje/v32y2001i1p101-28.html.

Hausman, J.A., Hall, B.H., Griliches, Z., 1984. Econometric models for count data with an application to the patents-r&d relationship.

Hegde, D., Herkenhoff, K.F., Zhu, C., 2022. Patent Publication and Innovation. Working Paper 29770. National Bureau of Economic Research.

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

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

Iacovone, L., Keller, W., Rauch, F., 2011. Innovation responses to import competition. Unpublished manuscript.

Jensen, M.C., Black, F., Scholes, M.S., 1972. The capital asset pricing model: Some empirical tests, in: Studies in the Theory of Capital Markets. Praeger Publishers Inc.

Jovanovic, B., Rousseau, P.L., 2005. General Purpose Technologies, in: Aghion, P., Durlauf, S. (Eds.), Handbook of Economic Growth. Elsevier. volume 1, pp. 1181–1224.

Kang, B., Bekkers, R., 2015. Just-in-time patents and the development of standards. Research Policy 44, 1948–1961. URL: https://www.sciencedirect.com/science/article/pii/S0048733315001146, doi:https://doi.org/10.1016/j.respol.2015.07.001.

Katz, M.L., Shapiro, C., 1985. Network externalities, competition, and compatibility. American Economic Review 75, 424–440.

Katz, M.L., Shapiro, C., 1986. Technology adoption in the presence of network externalities. Journal of Political Economy 94, 822–841. URL: http://www.jstor.org/stable/1833204.

Katz, M.L., Shapiro, C., 1994. Systems competition and network effects. Journal of Economic Perspectives 8, 93–115. URL: https://www.aeaweb.org/articles?id=10.1257/jep.8.2.93, doi:10.1257/jep.8.2.93.

Kelly, B., Papanikolaou, D., Seru, A., Taddy, M., 2021. Measuring technological innovation over the long run. American Economic Review: Insights 3, 303–20. URL: https://www.aeaweb.org/articles?id=10.1257/aeri.20190499, doi:10.1257/aeri.20190499.

Kindleberger, C.P., 1983. Standards as public, collective and private goods. Kyklos 36, 377–396.

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

Kuhn, J., Younge, K., Marco, A., 2020. Patent citations reexamined. The RAND Journal of Economics 51, 109–132. URL: https://onlinelibrary.wiley.com/doi/abs/10.1111/1756-2171.12307, doi:https://doi.org/10.1111/1756-2171.12307, arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1111/1756-2171.12307.

Leland, H.E., 1979. Quacks, lemons, and licensing: A theory of minimum quality standards. Journal of Political Economy 87, 1328–1346.

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

Llanes, G., Poblete, J., 2014. Ex ante agreements in standard setting and patent-pool formation. Journal of Economics & Management Strategy 23, 50–67.

Ma, S., 2021. Technological Obsolescence. Working Paper 29504. National Bureau of Economic Research.

Madsen, J.B., 2010. The anatomy of growth in the oecd since 1870. Journal of Monetary Economics 57, 753–767.

Martinez, C., 2010. Insight into Different Types of Patent Families. Working Paper 2010/02. OECD Science, Technology and Industry.

Mitchell, M.L., Stafford, E., 2000. Managerial decisions and long-term stock price performance. The Journal of Business 73, 287–329.

Mrázová, M., Neary, J.P., Parenti, M., 2021. Sales and markup dispersion: Theory and empirics. Econometrica 89, 1753–1788.

Nicholas, T., 2008. Does innovation cause stock market runups? evidence from the great crash. American Economic Review 98, 1370–96.

Pakes, A., 1985. On patents, r & d, and the stock market rate of return. Journal of political economy 93, 390–409.

Pakes, A., Schankerman, M., 1984. The rate of obsolescence of patents, research gestation lags, and the private rate of return to research resources, in: Griliches, Z. (Ed.), R&D, Patents, and Productivity. University of Chicago Press, pp. 73–88.

Pakes, A.S., 1986. Patents as Options: Some Estimates of the Value of Holding European Patent Stocks. Econometrica 54, 755–784. URL: https://ideas.repec.org/a/ecm/emetrp/v54y1986i4p755-84.html.

Perla, J., Tonetti, C., 2014. Equilibrium imitation and growth. Journal of Political Economy 122, 52–76.

Romer, P.M., 1990. Endogenous Technological Change. Journal of Political Economy 98, 71–102.

Rysman, M., Simcoe, T., 2008. Patents and the Performance of Voluntary Standard-Setting Organizations. Management Science 54, 1920–1934.

Schankerman, M., 1998. How valuable is patent protection? estimates by technology field. The RAND Journal of Economics 29, 77–107.

Schmalensee, R., 2009. Standard-setting, innovation specialists and competition policy. The Journal of Industrial Economics 57, 526–552.

Schmidheiny, K., Siegloch, S., 2023. On event studies and distributed-lags in two-way fixed effects models: Identification, equivalence, and generalization. Journal of Applied Econometrics 38, 695–713.

Schmidt, J., Steingress, W., 2022. No double standards: Quantifying the impact of standard harmonization on trade. Journal of International Economics 137, 103619. URL: https://www.sciencedirect.com/science/article/pii/S0022199622000514, doi:https://doi.org/10.1016/j.jinteco.2022.103619.

Seegmiller, B., Papanikolaou, D., Schmidt, L.D., 2023. Measuring document similarity with weighted averages of word embeddings. Explorations in Economic History 87, 101494.

Shapiro, C., Varian, H.R., 1999. The art of standards wars. California Management Review 41, 8–32.

Spulber, D.F., 2019. Standard setting organisations and standard essential patents: Voting and markets. The Economic Journal 129, 1477–1509.

Szewczyk, S.H., Tsetsekos, G.P., Zantout, Z., 1996. The valuation of corporate r&d expenditures: Evidence from investment opportunities and free cash flow. Financial Management , 105–110.

Traina, J., 2018. Is aggregate market power increasing? production trends using financial statements. Production Trends Using Financial Statements (February 8, 2018) .

Waguespack, D.M., Fleming, L., 2009. Scanning the commons? evidence on the benefits to startups participating in open standards development. Management Science 55, 210–223.

Webb, M., Short, N., Bloom, N., Lerner, J., 2018. Some facts of high-tech patenting. Working Paper w24793. National Bureau of Economic Research.