Innovation, Technology Standardization and the Value of the Firm

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Abstract

Technology standards are defined by national and international organizations to select and diffuse the best technologies and practices. By using a measure of patent novelty and a new measure of semantic proximity of patents to standards' documents, this paper exploits the process of standardization to disentangle the different contribution of innovation and diffusion to the value of the firm. The grant of an innovative patent raises a firm's market value up to 6% over a 10-year horizon. If thereafter the same patent and its underlying technology is included in a standard, the market value of the firm increases by an additional 3%, otherwise it declines. We show that the increase in value explained by innovation and diffusion (through standardization) are respectively due to productivity gains and rent extraction through higher markups.

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1 Introduction

The interplay between technological innovation and firm value is a well-established fact in the empirical literature on innovation, asset prices, and corporate finance. In fact, a large body of evidence has broadly shown that when a firm releases a new technology, its value increases as markets react positively to the grant of the patent describing the novel invention (among others, see Kogan et al., 2017). Typically, the positive short-term adjustment in share prices reflects a combination of investors' "hype" about the new patented technology, its commercial potential and higher expectations of future revenues and growth (Pakes, 1985, Pakes, 1986).

However, whether the initial positive sentiment and momentum is then justified by sustained economic performances is a discriminant factor for the success of that innovation and, consequently, for the long-run value of the firm. For this to happen, the widespread adoption and diffusion of the patented technology is fundamental. The fact that a new technology is preferred to others and becomes broadly used over time not only certifies the quality of that innovation, but also determines which firms operate at the frontier and which are lagging behind. This, in turn, generates heterogeneous trajectories in revenues, growth, and profitability across firms (Jaffe, 1986): laggards incur adoption and reorganization costs that –at least in the short-run– affect their competitiveness, market shares and profits which shift in favor of leaders (Blundell et al., 1999). Hence, whether a new technology diffuses or not is an important corporate event that goes beyond the positive implications of innovation and patenting activity and the initial reaction of financial markets.

While the literature has explored the consequences of innovation for firm valuation, the impact of diffusion is understudied – largely due to the lack of convincing measures of industry-wide technology adoption. This paper closes the gap and disentangles the contribution of technological innovation and diffusion to firm value, both in the short and in the long run. In particular, we show that although high-quality inventions are immediately rewarded by financial markets through stock-price appreciation, only those innovations that subsequently diffuse allow firms to maintain or further increase their value over a longer horizon. By doing so, the paper highlights the importance of the diffusion margin for asset prices and firm value in the long-run. Moreover, it provides evidence that markets do not have perfect foresight over the diffusion process and cannot price correctly innovation (see Cohen et al., 2013): they tend to over-react to the release of a new technology, but cannot immediately price in its subsequent adoption and diffusion as this remains uncertain.

The main contribution of the paper lies in the identification of the innovation and diffusion margin, which is empirically challenging. In fact, if on one hand, the grant date and quality of a new patent can plausibly be treated as exogenous information shocks that are not anticipated by markets, on the other hand, the process of diffusion is in-

herently endogenous and observable at any point in time. To overcome this problem, we exploit a specific mechanism of technological diffusion that allows us to treat the broad adoption of a technology as a quasi-experiment. This mechanism is *technology standardization*, namely the definition and promotion of *technology standards*.

Technology standards are pervasive in industrial societies, and every sector heavily relies on them for the development and production of new goods and services. In fact, essentially all technologies that we use on a daily basis –from e-mails to a 5G connection, from a USB-C pen to online payments– rely on technical specifications defined by standards. Standards are managed by national or international standard-setting organizations (SSOs), e.g. the International Organization for Standardization (ISO), which ensure the definition and diffusion of the best practices and technology at the industry level (see Katz and Shapiro, 1985, Farrell and Saloner, 1985). In this sense, technological standardization inherently involves the selection of one technology over competing alternatives and promotes its widespread adoption. By doing so, SSOs not only acknowledge high-quality innovations, but also facilitate their technological diffusion by reducing information frictions, ensuring interoperability and compatibility, coordinating future R&D efforts, and generating spillovers and network externalities that benefit both firms and consumers (see Rysman and Simcoe, 2008).

Most importantly for our identification purposes, the institutional procedures and internal rules governing SSOs ensure that the technical features of the new standardized technologies are not publicly disclosed prior to official communication by SSOs. In fact, while markets and firms observe the existence and quality of incumbent patents and technologies, they do not have perfect knowledge of which technologies will ultimately be selected for standardization. This allows us to interpret and use the publication of a new standard as the beginning of the diffusion process of a specific technology, since firms then have immediate incentives to comply with the standard and adopt the standardized technology in order to remain competitive (see Schmidt and Steingress, 2022). Given this institutional setup, whether a firm sees its patented technology being included into a standard (or not) is economically important, as standardization can provide a competitive advantage from patent ownership relative to direct competitors. In fact, as shown in Bergeaud et al. (2026b), firms that own patents included in a standard see their market share and sales temporarily increase as their competitors need to adapt and reorganize around the newly standardized technology.

In light of this, we leverage both the grant date of new patents and the release date of new standards to study the distinct contributions of innovation and technology diffusion –through the process of standardization– to the value of the firm. By doing so, we can disentangle the different roles played by innovation and diffusion from the moment a new technology is invented to the moment it becomes part of a standard and beyond. To our knowledge, this is the first paper that attempts to separate and quantify these two margins. The process of standardization is crucial to do so as it allows us

to discretely split the life-cycle of a new technological patent into two periods: before the (eventual) inclusion of the patent into a standard, i.e. when the new technology is patented and enters in competition with existing ones; after standardization, when the technology is selected for diffusion and adoption at the industry level.

Conducting this analysis requires knowledge of i) firms' innovation output and its quality; and ii) the extent to which each innovation is incorporated into a standard later on. For the former, we rely on patent-level data and use a measure of innovation quality from Kelly et al. (2021) that captures both the novelty and relevance of a new patented technology. For the latter, we use documents approved by industry experts from SSOs that describe the basic features of the selected technology (known as *standards*). Prominent examples are mobile telecommunication standards (such as the 5G standard family) or Internet protocols. Then, we match the semantic content of (previously granted) patents to newly released standard documents in order to measure the extent to which the content of a patent overlaps with that of a standard. In other words, this measure of semantic proximity tells how much the features of a technology patented by a firm are included in the new standard and –therefore– to what extent the new patented technology has the potential to diffuse since the publication of the related standard onwards (see Bergeaud et al., 2026b).

Equipped with these patent-level measures, we conduct our analysis both at the patent and firm-level. At the patent level, we document three facts.

First, consistent with the institutional functioning of SSOs, we show that the majority of firms start issuing patents that resemble the new standard only after its publication. This result is fundamental as it proves that i) prior to the standard release, each firm is on its own independent innovation trajectory, and there is no diffusion of the standardized technology before the release of the standard despite the quality of patents ultimately included into a standard is always observable; ii) the release of a standard removes an information friction, inducing firms to produce patents closer to the standard (i.e. with features similar to those in the standard) only after its publication; iii) most of this convergence and adoption process is explained by followers, i.e. firms that originally did not have patents aligned with the newly published standard.

Second, we show that SSOs tends to include into new standards patents that originally were novel and relevant. However, the novelty and relevance of a patent –as perceived at its grant date– do not predict its inclusion in a future standard. This is an important result since it validates the fact that –under this setup– innovation and diffusion through standards can be treated separately as uncertainty around which technology will be included into the standard despite innovation quality being always observable.

Third, for each patent and publicly listed firm in COMPUSTAT and CRISP, we use daily stock market data and study returns around the patent grant date (innovation margin) and around the standard publication date when the patent is included into a new standard (diffusion margin). We find that markets react positively at both dates.

However, there is an important caveat. At the patent grant date, the market reaction is stronger the higher is the novelty and relevance of the new innovation. On the other hand, the observed returns at the patent grant date are uncorrelated with our measure of proximity to future standards. In other words, at the grant date, markets are unable to price and foresee the potential of future diffusion of a new patented technology. Conversely, at the standard publication date, returns are larger for those firms whose patents are technologically closer to the new standard. Yet, these returns are unrelated to the original novelty of the patent, whose quality is already priced in at the patent grant stage. Simply put, being the quality of patents already observed and discounted, at the moment of the standard release markets price the extent to which a patent has the potential to diffuse in the future. This information is priced in only at the standard publication date (not at the patent grant date).

Finally, based on this high-frequency analysis, we conduct a back-of-the-envelope calculation and show that producing a patent of mean quality leads to an increase in the firm market value by 0.3% on the day of patent grant. If the same patent is later on included into a standard, the market value of the firm increases by 0.2% at the standard publication date. In other words, when looking at stock market reactions, the innovation margin explains 60% of the overall increase in market value, while the rest is due to the diffusion margin (throgh standardization).

Thereafter, we proceed with the aggregation of these measures at the firm level and study the dynamic contribution of innovation and diffusion to the value of the firm at quarterly frequency and over a long horizon. In particular, here we look at both market and book (accounting) value of the firm. In fact, if on one hand the market value reflects more expectations on future economic profits and better captures the value of intangibles, on the other hand the book value tracks already reinvested profits and realized growth. Hence, considering both the market and book value allows us to better grasp how the innovation and diffusion margins affect firm's dynamics and the process of value generation (see Eisfeldt and Papanikolaou, 2013 and Gerakos and Linnainmaa, 2018).

In light of this, our analysis proceeds as follows. As patents and standards can be released in multiple consecutive periods and firms can publish a new patent while contemporaneously having older patents included in a new standard (and vice versa), we use a dispersed lead-lag model with both margins of innovation and diffusion. In the spirit of Hall et al. (2005), this "horse-race" analysis between the two margins allows to identify the effect of patenting activity netting out the contemporaneous effect of standardization (and vice versa). Moreover, with respect to a static analysis, the lead-lag component allows to capture the full dynamics of the response following either the release of a new patent or a new standard. Our results show that the release of a high-quality patent generates persistent positive effects on both the market and the book value of the firm. By contrast, firms whose patents become technologi-

cally aligned with newly released standards experience positive but more temporary increases in the firm's value. Moreover, the market value of the firm is more sensitive to both margins than the book value. This suggests that –although innovation and technology diffusion allow the firm to grow in book-value terms– most of the value increase following a patent grant comes from market valuation and higher expectations of future earnings.

As done in the patent level analysis, we conduct a back-of-the-envelope calculation that quantifies the cumulative contributions of innovation and standardization in the long run (12 years) while accounting for the time-delay between patent grants and subsequent standard inclusion, which is on average 10 years. We find that the firm's value increases persistently following the release of a high-quality patent. However, these gains deteriorate or flatten out when the patent is not eventually incorporated into a standard and therefore fails to diffuse through this channel. In particular, the market value of the firm increases up to 6% over the ten years following the release of a promising patent, but it declines thereafter, converging to roughly 5% in the long run (i.e. up to 17%). By contrast, if the patent is eventually incorporated into a standard after 10 years, the market value increases by an additional 3% (i.e. to 9%) and does not subsequently decline. In other words, technological diffusion through standardization accounts for up to 40% of the total cumulative increase in the firm market value associated with the invention of a successful technology. When we focus on the book value of the firm, we find that it increases rapidly in the first ten years following the release of a promising patent, and then its growth flattens out in the subsequent years up to 12%. Conversely, if the patent is incorporated into a standard, the book value grows by an additional 5 percentage points in the long run. Hence, we conclude that technological diffusion through standardization accounts for up to 30% of the total cumulative increase in the book value of the firm.

In the final part of the paper, we investigate the economic mechanisms underlying the innovation and diffusion margins and the channels through which they affect firm value. Our results show that while producing high-quality technologies generates firm-level productivity gains, it is through technological diffusion that firms are ultimately able to monetize their R&D investments and extract rents through higher markups.

All in all, these results demonstrate that high-quality innovation is only a necessary but not sufficient source of economic value. Technological diffusion is key for the firm to continue growing and to maintain or increase its value in the long-run.

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

The first strand concerns the relationship between innovation, firm value, and asset prices. Existing studies rely on two main approaches to measure innovation activity

and assess its implications. The first focuses on R&D expenditures. For example, Chan et al. (1990), Szewczyk et al. (1996), and Eberhart et al. (2004) show that firms experience positive abnormal returns and increases in share value following announcements of unexpected R&D investment plans. However, R&D expenditure primarily captures the financial effort devoted to innovation rather than the quantity or quality of innovative output itself.

To address this limitation, a second strand of the literature focuses directly on innovation outputs, particularly patents and patent quality. Hall et al. (2005) show that patent citations provide an effective measure of the quality and relevance of inventions, to which financial markets react accordingly. Similar findings are reported by Kogan et al. (2017), Pakes (1985), Austin (1993), Nicholas (2008) and Hirshleifer et al. (2018), who document positive stock market reactions to the issuance of high-quality patents. In line with this literature, our paper exploits the patent quality measure developed by Kelly et al. (2021), which captures both the novelty and future relevance of newly granted patents –namely, patents whose technological features are unprecedented and subsequently become influential for future innovation.

Our paper also differs from much of the existing literature, which primarily focuses on short-term market reactions. In fact, we examine both the short and long-term effects of innovation on firm value by considering not only stock prices and returns, but also the evolution of firms' book and market value over time. This approach allows us to provide evidence on how patents generate value throughout different phases of their life cycle: at issuance ("birth"), during diffusion ("take-off"), and when eventually superseded by newer technologies ("maturity"). In this respect, our work also relates to the literature on innovation and creative destruction (e.g., Romer, 1990; Aghion and Howitt, 1992; Grossman and Helpman, 1991) as well as the literature on the "S-curve" of technology diffusion (see Geroski, 2000 for a review).

Because we exploit technology standards to study the extent to which patents diffuse and underlying technologies are adopted, the second strand of literature we contribute to concerns standardization. Technology standards have long attracted attention in the industrial organization literature (see Kindleberger, 1983 for a historical overview), which has emphasized the benefits of standardization mechanisms. By fostering interoperability, compatibility, and network effects (Katz and Shapiro, 1985; Farrell and Saloner, 1985), reducing transaction costs, and mitigating information asymmetries (Leland, 1979), standardization plays a central role in the large-scale diffusion and deployment of technologies. Standard-setting organizations (SSOs) are therefore crucial actors in this process (Rysman and Simcoe, 2008), particularly for the industry-wide adoption of general-purpose technologies (Basu and Fernald, 2008; Jovanovic and Rousseau, 2005).

These mechanisms also have important macroeconomic implications. Bergeaud et al. (2026b) show that, in the short run, standards provide a competitive advantage to firms

already owning technologies selected for diffusion by SSOs as they can immediately deploy, scale and market new products in line with new standards. This advantage translates into temporary increases in sales and market shares. In the longer run, however, knowledge spillovers induce lagging firms to innovate, catch up with industry leaders, and eventually surpass them, thereby fostering sectoral growth.

Finally, our work contributes to the growing literature on text mining and semantic analysis applied to patents and standards. Text-mining techniques are increasingly employed in economics –particularly in innovation economics– for the analysis of patent data (see Abbas et al., 2014 and Bergeaud et al., 2026a for an overview). Existing studies use patent semantics to measure patent similarity (Arts et al., 2018; Kuhn et al., 2020), identify patents related to specific technologies (Bergeaud and Verluise, 2022; Dechezleprêtre et al., 2021; Bloom et al., 2021), classify patents (Bergeaud et al., 2017; Webb et al., 2018; Argente et al., 2020), and measure patent novelty (Kelly et al., 2021).

The paper is organized as follows: Section 2 briefly describes the institutional frameworks of SSOs and our empirical strategy; Section 3 and 4, provide data description, empirical analysis and results both at the patent- and firm-level; Section 5 concludes.

2 Institutional framework and identification

2.1 Standards in brief

Similar to a patent, a standard is a document that describes certain features of a product, a production process, a protocol, or a technology. Contrary to patents that are filed by individual inventors or firms, standards are developed by standard-setting organizations (SSOs). Typically, SSOs are non-profit organization which gather industry experts from both the private and public sector in working groups and technical committees dedicated to the definition and approval of a new standard (Spulber, 2019, Schmalensee, 2009). The approval requires multiple rounds of revisions and refinements of the standard documents which must be voted by a judging commission and all participants in the standard process.[1] Only once the final version is approved, the standard is finally published in the SSO gazette. Well-known examples of SSOs are the International Organization for Standardization (ISO), national standard bodies such as DIN (Deutsches Institut für Normung) or industry associations such as IEEE (Institute of Electrical and Electronics Engineers).

It is important to stress that standards are not defined to merely recognize the quality of some specific innovation over others or to ratify a technology that has already achieved widespread adoption and diffusion (*ex-post standardization)*. Conversely, their

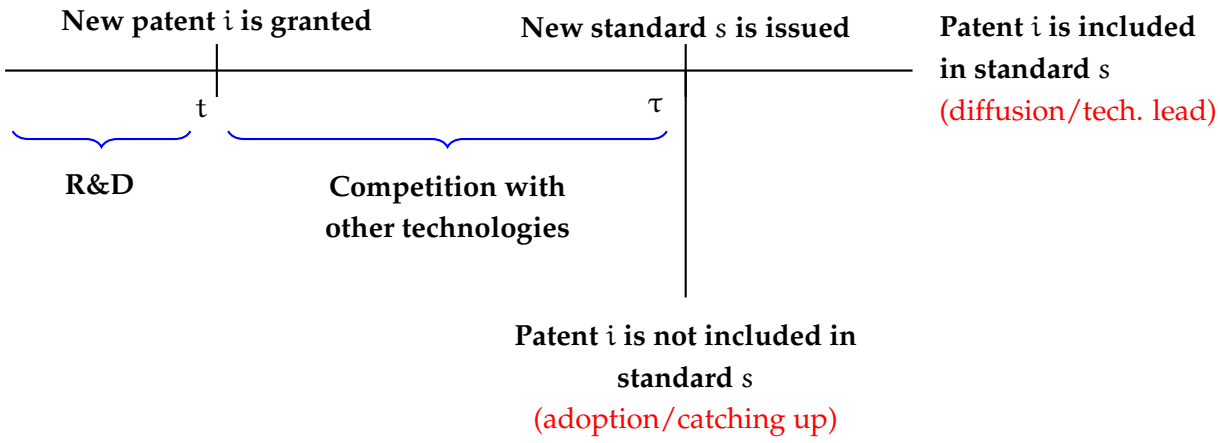
[1]For this reason they are often called *consensus standards*.

primary goal is rather to reduce information frictions and coordinate industry participants around a technology not yet diffused, so that its collective adoption generates efficiency gains (Leland, 1979) as well as vertical and horizontal synergies through the production of mutually compatible goods and services (*ex-ante standardization*). In this sense, a standardized technology is distinguished not only by its technical and innovative merits, but also by its satisfaction of criteria such as interoperability, compatibility, scalability, and efficiency (Katz and Shapiro, 1985; Farrell and Saloner, 1985). Therefore, through the definition of standards, SSOs point the technological direction firms should take. This helps create a common technological field that all industry participants can build upon efficiently and competitively. Hence, the creation of the standard will not only stimulate the adoption of the superior technologies, but also foster sectoral competition and growth (see Bergeaud et al., 2026b), thus preventing the rise of monopolistic power or technological lock-in at sectoral level.

In light of this, if patents are the output of innovation activity, standards are formal mechanisms to boost the diffusion of those (not-yet adopted) innovations capable of generating more spillovers and synergies, and to open more market opportunities for firms. Therefore, the patents chosen as the foundation of a new standard are evaluated not only on their technical quality, but also on the broader economic and competitive advantages their widespread adoption would unlock.

2.2 Identifying the effect of innovation and diffusion through standards

Figure 1: FROM PATENT GRANT TO INDUSTRY ADOPTION THROUGH STANDARDIZATION



Notes: This figure sketches the events following the grant of a patent at time t. Following the patent grant, the technology described in the patent is eventually included in a new standard issued at time τ. If this is the case, the technology described in the patent is adopted at the industry level and diffuses, and the owner of that patent becomes temporarily a technological leader.

Since neither the date of patent grant nor the content and publication date of a standard are perfectly predictable, we can exploit the timing of patent and standard releases to

identify and disentangle the distinct contributions of innovation and diffusion –the latter operating through the standardization process– to firm value. Figure 1 summarizes the key corporate events and the paths a firm may follow.

Following a period of R&D investment, a firm may be granted patent i at some point in time t. From that moment, the patent and the underlying technology enter into competition with existing patents and technologies from other firms. Throughout this phase, the quality of the patented technology remains observable to all market participants, including SSOs. Should the technology not be widely adopted, but instead be deemed superior and satisfy criteria such as interoperability, compatibility, and network effects, SSOs may consider it for standardization. After a standard development and approval process spanning several years, the technology may eventually be standardized at time $\tau > t$ –that is, the technical features of patent i are incorporated into standard s. When this occurs, the technology begins to diffuse at the industry level, and the firm owning the relevant patent gains a technological lead. As documented in Bergeaud et al. (2026b), firms holding patents aligned with a newly issued standard enjoy a temporary competitive advantage following its release, as they can immediately deploy, scale, and commercialize applications built on the standard. By contrast, firms without patents or technologies aligned with the new standard face strong incentives to adopt them in order to remain competitive (see the discussion in Schmidt and Steingress, 2022) and to market their products in accordance with the standardized technology.

Our patent data and semantic analysis allow us to identify: i) which firms innovate, the quality and scientific relevance of their innovation; and ii) which firms see their technologies being included in a new standard and to what extent. By exploiting the heterogeneity in innovation capacity and standardization outcomes – together with variation in the timing of patent grants t and standard releases τ– we are able to identify the contribution of innovation and technology diffusion (through the process of standardization) to the value of the firm. As we discuss in detail below, identification rests critically on two conditions: the timing cannot be perfectly predicted, and uncertainty remains about the granting of the patent and the details of the standard until their respective publication. Consequently, neither markets nor firms can anticipate or perfectly predict the content of a new standard, even though patent quality remains continuously observable.

3 Patent-level analysis

3.1 Patent-level data

Our patent-level and firm-level analysis relies on two measures: *Novelty* and *Proximity*. The first captures the novelty, relevance and influence of a newly issued patent on future research and is drawn directly from Kelly et al. (2021). The second is our own

measure, introduced in Bergeaud et al. (2026b), and quantifies the degree to which a patent is semantically close to a newly issued standard. In this section, we briefly describe both variables and refer the reader to the respective papers and Appendix A and B for further details.

Novelty and relevance of a patent. Kelly et al. (2021) draw on patent data from which they extract keywords describing each underlying invention. To measure whether a new patent represents a genuine technological novelty, they proceed as follows. For each patent i published at time t, they record how frequently each keyword w_k appearing in patent i also appears elsewhere in the corpus of all patents published up to time t. Formally, for each keyword w_k, they define the term frequency $TF(w_k)$ as the number of times the keyword appears in the description of patent i, and the backward-looking inverse document frequency $BIDF_t(w_k)$ as a measure of how uncommon keyword w_k is across the full corpus of patents published up to time t. On this basis, they construct the following measure of backward cosine similarity between patent i and any other patent l:

$$\rho(i,l)_t^{BACK.} \equiv \frac{\mathcal{B}(i)\cdot\mathcal{C}(l)}{\|\mathcal{B}(i)\|\,\|\mathcal{C}(l)\|} = \frac{\sum_{k=1}^{K}\mathcal{B}(i)_k\mathcal{C}(l)_k}{\sqrt{\sum_{k=1}^{K}\mathcal{B}(i)_k^2}\cdot\sqrt{\sum_{k=1}^{K}\mathcal{C}(l)_k^2}}$$

where $\mathcal{B}(i)$ and $\mathcal{C}(l)$ are respectively the set of keywords characterizing patent i and l; $\mathcal{B}(i)_k$ and $\mathcal{C}(l)_k$ are the k-th components of vectors $\mathcal{B}(i)$ and $\mathcal{C}(l)$, which represent the weighted occurrence of k-grams in patent i and patent l, respectively. The vectors span the union of all k-grams found in either document: $\mathcal{K} = \{\mathcal{B}(i) \cup \mathcal{C}(l)\}_{i,l}$. To account for the informational value of each term, they define: $\mathcal{B}(i)_k = BIDF(w_k^B)\cdot TF(w_k)$ and $\mathcal{C}(j)_k = BIDF(w_k^C)\cdot TF(w_k)$.

Given this, they define Ω_t the set of all patents l published five years prior to t, i.e. before the publication date of patent i. Hence, the overall "backward similarity" of patent i with respect to older patents is:

$$BS(i)_t = \sum_{l\in\Omega_t}\rho^{BACK.}(i,l)_t$$

such that a small value of $BS(i)_t$ implies that patent i has introduced some novel and unprecedented technology.

To look at the relevance of a patent, i.e. how much later patents are similar to the patent published today, Kelly et al. (2021) look at forward similarity. Following the same procedure, one can study the similarity of patent i with all patents l published

after time t. By substituting $BIDF(w_k)$ with the forward-looking inverse document frequency $FIDF(w_k)$ in the cosine-similarity definition above, we can define forward cosine-similarity measure between patent i and subsequent patent l as $\rho^{FOR.}(i,l)_t$. Hence, the overall "forward similarity" of patent i with respect to more recent patents is:

$$FS(i)_t = \sum_{l \in \Gamma_t} \rho^{FOR.}(i,l)_t$$

where Γ_t is the set of patents issued up to one year following the release of patent i at time t.[2] Consequently, a big value of $FS(i)_t$ implies that patent i has become relevant for future research and innovation immediately after its publication.

Finally, given these metrics, we follow their methodology and build a measure of novelty and relevance of patent i as

$$Novelty_{i,t} = \frac{FS(i)_t}{BS(i)_t}$$

such that the higher is this variable the more novel and relevant is the technology described in patent i published at time t.

This variable is not bounded. Hence, we rescale it between 0 and 1 for convenience and interpretability.

Proximity of a patent to a new standard. If for patent data collection and manipulation we proceed closely to Kelly et al. (2021) and Kogan et al. (2017), for standards we use the Searle Center Database on Technology Standards and Standard Setting Organizations (see Appendix A and Baron and Spulber, 2018 for more details). This data is largely based on `Perinorm`, a bibliographical database of product standards whose purpose is to provide subscribers with basic information on the standard. Our database covers all types of standards for a large number of industrialized countries. `Perinorm` also contains keywords describing each standard, which we store. Hence, for each standard s, we define with $\mathcal{A}(s)$ the set of keywords describing the standard.

Hence, we define the patent-to-standard matching score by using the cosine similarity

[2] If in Kelly et al. (2021) forward similarity is built by using the pool of patents in the 5-year window after the patent grant, here instead we consider similarity to patents published only one year ahead. This allows to better grasp the novelty and relevance as perceived as close as possible to the patent grant date. We consider only one year ahead to avoid that forward similarity would immediately capture the inclusion of the patent in a standard (which on average occurs 9 years after the patent grant) and the consequent diffusion of that technology through standardization.

between patent i (granted at time t) and standard s (issued at time τ):

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

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

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

where $\text{IDF}(w_k^A)$ and $\text{IDF}(w_k^B)$ denote the inverse document frequency of keyword w_k across the entire corpus of standards and patents respectively, and $\text{TF}(w_k)$ is the term frequency of w_k within the patent abstract. Hence, the higher the value Proximity the closer is patent i to standard s. Notice that this measure is naturally bounded between 0 and 1. Moreover, at this stage we allow τ to be both bigger or smaller then t, i.e. we consider all possible scores from matches of patents with newer or older standards. For more details and discussion, see Appendix B.

Final dataset for patent-level analysis. Combining these measures yields a dataset of patent-standard observations spanning 1980 to 2010. For each patent i granted at time t, we observe the full list of standards to which it is matched –whether released before or after the patent grant (i.e. $\tau < t$ or $\tau > t$)– together with the corresponding *Proximity* and *Novelty* score. Using the crosswalk from Kogan et al. (2017), we link patent identifiers to Compustat and CRSP identifiers, allowing us to establish patent ownership and retrieve stock market prices and excess returns for each firm around both the patent grant date and the standard release date. We retain only the subsample of patents for which all of this information is available.

The resulting final sample comprises approximately 3,000 firms, 110,000 patents, 302,000 standards, and 4 million patent-standard pairs. Table 1 reports summary statistics. The average patent has a *Novelty* score of 0.18 and its distribution is skewed to the right with few values between 0.3 and 1. When looking at the within-firm average *Novelty* across new issued patents, the distribution of the variable is almost identical. The average patent has a *Proximity* score of similar mean, but its distribution is more skewed to the right: half of patents do not match any standard (i.e. *Proximity* $= 0$). Moreover, when looking at the within-firm average *Proximity* across all matched standards, the mean is just 0.07: most patent-to-standard matches at the firm level are thus zero or

close to zero, with sizable *Proximity* scores appearing only above the 75th percentile. Taken together, this indicates that close alignment with a standard is rare, and that most firm-level patents bear little or no proximity to any standard.

When considering patents released prior to the matching standard, we find that the average time-lag between patent and standard publication is 9 years. Conversely, for patents released after a standard, the average time lag is 14 years. The average number of patents matching a (new or old) standard is 13. Also, conditioning on positive *Proximity* scores, the average number of patents per standard is 7, with the median standard matching only up to 4 patents. This, along with the skewed distribution of the *Proximity* variable, the fact that half of all matches are zero, and that most firms match positively with only a few standards, is an important feature of the data. We will take this into account when aggregating patent-level scores to the firm level.

Table 1: DESCRIPTIVE STATISTICS FOR PATENT-LEVEL DATA

	Mean	SD	p1	p5	p25	p50	p75	p95	p99	N
Novelty	0.18	0.04	0.12	0.13	0.15	0.17	0.19	0.25	0.34	109,329
Within firm mean Novelty across patents	0.18	0.05	0.12	0.13	0.15	0.17	0.19	0.26	0.36	3,089
Proximity	0.18	0.22	0.00	0.00	0.00	0.15	0.32	0.59	0.85	4,029,960
$\mathrm{I}(\text{Proximity} > 0)$	0.50	0.50	0.00	0.00	0.00	1.00	1.00	1.00	1.00	4,029,960
Within firm mean Proximity across standards	0.07	0.18	0.00	0.00	0.00	0.00	0.00	0.49	0.83	3,089
Time to standard $(\tau - t) > 0$	9.13	7.39	0.00	0.00	3.00	7.00	13.00	24.00	31.00	1,815,903
Time from standard $(\tau - t) \leqslant 0$	14.11	10.58	1.00	1.00	6.00	12.00	20.00	35.00	43.00	2,214,057
N. of patents per standard	13.36	22.16	1.00	1.00	2.00	6.00	15.00	50.00	110.00	301,576
N. of patents per standard & $\mathrm{I}(\text{Proximity} > 0)$	7.60	10.99	1.00	1.00	2.00	4.00	9.00	26.00	52.00	266,111

Notes: This table reports descriptive statistics at the patent level for the variable *Novelty* and *Proximity* along with information on the time between the release of a patent and a matching standard, and the number of patents matching a single standard. See Section 3.1 fo more details on data construction and variables definition.

3.2 Patent-level analysis and results

In this section, we show three facts. First, firms do not anticipate the specific technological content of an upcoming standard and therefore react and adjust their innovation strategies only after the standard is published. In particular, firms whose existing technological portfolios are initially distant from the newly adopted standard increase their R&D efforts to align with it only after its release. This finding suggests that, although technological diffusion is endogenous and patent quality is publicly observable, firms cannot predict ex ante which technologies will ultimately be standardized or which features a new standard will embody. Hence, the publication of a new standard removes an information friction: firms learn in which direction to innovate and act accordingly only after the new standard is released.

Second, high-quality innovation does not necessarily translate into diffusion through standardization, i.e. our measure of *Novelty* correlate but does not predict *Proximity*. Put differently, although standards features specifics from the most innovative patents, it is not true that the most novel and relevant technologies (as perceived at the issuance of the corresponding patent) are always included into a new standard. This lack of

predictability is clear when looking at financial markets and prices. Although financial markets respond positively to the grant of innovative and relevant patents, they are unable to foresee and immediately price in whether those patents will later be incorporated into a standard and diffuse. This finding highlights the limits of market efficiency and long-run foresight. In fact, markets react positively also when a firm has a patent close to a newly issued standard. Taken together, these results indicate that markets are able to price the intrinsic quality of an innovation as soon as the patent is granted, but they cannot immediately price the likelihood that the technology will prevail over competing alternatives and subsequently become embedded in an industry standard and diffuse. This former information becomes available only at the release of a new standard.

Finally, we quantify the economic value generated by these two distinct events. We estimate the impact on the firm market value of introducing a novel technology at the time the corresponding patent is granted, and we measure the additional revaluation that occurs when the same patent is subsequently incorporated into a newly issued standard and promoted for diffusion at the industry level.

3.2.1 Standards as information shocks

If the content of new standards were easily predictable, their release would not affect firms' innovation choices. In fact, if this were the case, firms would preemptively take action and conduct innovation in the right direction even before the release of a new standard. In this section we show that this is not true: a new standard releases new information and firms act accordingly only after the publication of the standard. In particular, once the standard is known, firms direct their innovation effort towards the technology described in the standard document. This process allows firms to align with the new technological frontier imposed by the standard and –at the same time– foster the adoption and diffusion of the standardized technology.

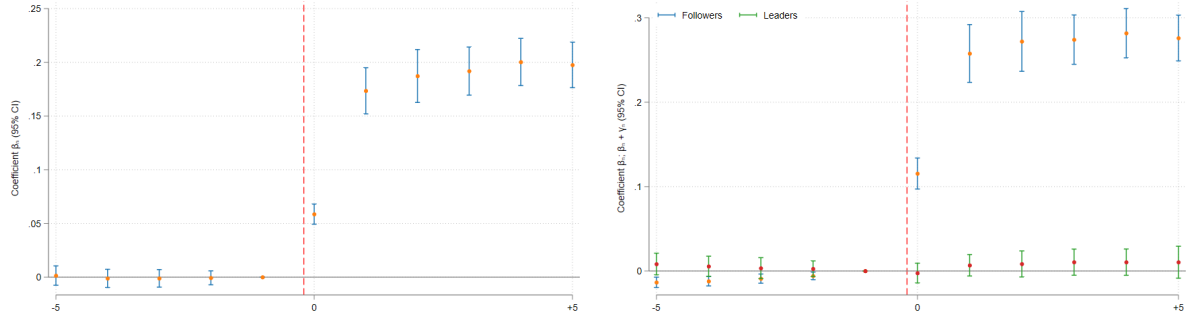
To show this, we use our patent-standard dataset as follows. For each standard s, we consider a time window around its publication date τ of +/- 5 years. Hence, we study the evolution of matching patents before and after the publication of the standard.

In particular, we use this model:

$$Proximity_{i,s,t} = \xi_s + \lambda_i + \sum_{n=-5}^{N=5} \beta_n \mathbb{I}[t = year_s + n] + \epsilon_{i,s,t} \quad (1)$$

where $Proximity_{i,s,t}$ denotes the similarity of patent i (granted in the calendar year t) with respect to standard s. ξ_s is a standard fixed-effect. λ_i is a dummy taking value one if patent i belongs to a leader, i.e. a firm having at least a patent matching standard s already before its publication. $year_s$ is the calendar year of the publication of standard

Figure 2: STANDARDIZATION AND SIMILARITY OF NEW PATENTS TO THE STANDARD



(a) New patents similarity (b) Leaders vs. Followers

Notes: Figure 2(a) and 2(b) plot the estimated coefficients of equation (1) and their decomposition between leaders and followers. The baseline year is the year prior to the publication of the standard (-1). The 95% confidence intervals for each point-estimate is reported. Standard errors are clustered at the standard level. The red-dashed indicates the period of publication of the standard.

s such that $\mathbb{I}[t = year_s + n]$ takes value one at the n^{th} year before/after the publication of the standard. Hence, by plotting each β_n (baseline $n = -1$), we will check if indeed the mean proximity of newly granted patents increases only after the publication of the standard.

As displayed in Figure 2(a), in the years prior to the release of a standard ($t < \tau$), new patents do not improve in quality in the direction that the future standard prescribes. In other words, firms are on their own innovation trajectory and all newly issued patents do not anticipate the features of the upcoming standard. Conversely, patents start to better match the new standard only after the standard publication. This allows us to conclude that the publication of a standard represents important information for firms as they learn which direction to take in their innovation activity. This leads to the production of new patents that are better in quality than pre-standard patents. By doing so, firms align with the new standard and support the diffusion of the standardized technology.

Given this, now we want to understand to what extent this result is driven by leaders and followers. For this reason, we interact the dummy $\mathbb{I}[t = year_s + n]$ with the dummy λ_i in order to decompose the effect between leaders and followers. Figure 2(b) plots these two separate margins. Notably, the observed increase in patent quality following the release of a new standard is due to followers. The new patents issued by leaders improve only marginally (and not always significantly).

All in all, this evidence confirms the following: i) most firms start issuing patents closer to the standard only after the publication of the standard; ii) this process of convergence is mostly explained by firms who were originally far away from the frontier, i.e. those with originally no patent matching the standard. In Bergeaud et al. (2026b) we provide in depth evidence that standards indeed boost the process of technological adoption and diffusion, and incentivize further innovation. This process of catching

up –mostly driven by technological laggards– boosts sectoral growth.

3.2.2 *Novelty* vs. *Proximity* and stock market reaction

If this evidence shows that firms cannot predict standards and their content, we now turn our attention to financial markets and investors. Specifically, we investigate three things. First, we study whether markets can use the novelty of an innovation to infer already from the grant date if that new technology is going to be incorporated into a future standard or not. Namely, we study the extent to which *Novelty* predicts *Proximity* and the probability for a patent to match a future standard based on its initial quality. Second, we study stock market's reaction around the patent grant and the standard release date and check if there is any surprise around both events. This is important to test if –beyond the market reaction observed around the patent grant date (e.g. as shown in Kogan et al. (2017))– the release of a standard represents new information for markets and investors. Third, we investigate the extent to which the market reaction observed at the patent grant and standard release date is explained by either the novelty of the patent, or by its proximity to a standard or both. This will clarify what type of information matters for markets and when. More importantly, this analysis will reveal whether markets fully anticipate and price innovation, its subsequent diffusion through standardization, or both already at the time of the patent grant and what metric (*novelty vs. proximity*) matters the most.

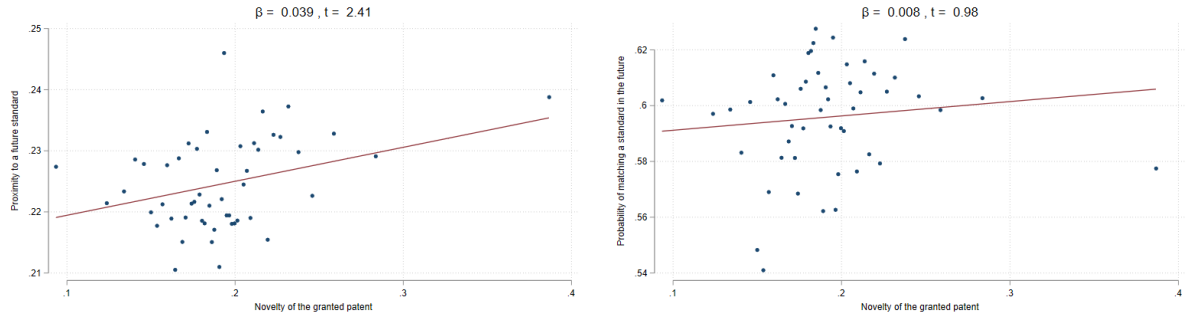
Addressing these questions allows us to assess whether innovation and diffusion through standardization constitute distinct corporate events that are valued separately by financial markets.

Novelty vs. Proximity We consider only patents issued prior to the release of a standard ($t < \tau$), and look at the correlation between our measure of *Proximity* and *Novelty* across all possible patent-standard matches while controlling for patent ownership and the date of patent grant. Formally, we consider the following:

$$Proximity_{i,s,\tau} = \alpha_{i(f)} + \theta_{i(t)} + \beta Novelty_{i,t} + \epsilon_{i,s,\tau} \tag{2}$$

where $\alpha_{i(f)}$ is the fixed effect indicating firm f as owner of patent i, whereas $\theta_{i(t)}$ is the time of release of the patent i. Figure 3(a) shows that there is a mild positive and significant correlation between the two measures: more innovative and relevant patents tend to better match standards in the future. Put in words, patents that later on will match well the content of a standard tend to be of higher novelty. This tells us also that, on average, SSOs define standards based on technologies that originally were novel and represented a discontinuity with the past. Yet, this does not mean that it is sufficient for a patent to be novel to be included into a (future) standard. To show this point, we

Figure 3: NOVELTY VS. PROXIMITY



(a) Novelty vs. Proximity

(b) Novelty vs. Pr(Proximity>0)

Notes: Figure 3(a) and 3(b) plot the estimated relationship of equation (2) when the dependent variable is *Proximity* or $I(Proximity_{i,s,\tau} > 0)$.

study if the probability to match a standard depends on the initial quality of the patent. To do so, we estimate equation (2) with $I(Proximity_{i,s,\tau} > 0)$ as dependent variable. As shown in Figure 3(b), there is no significant correlation between the novelty of a patent and the probability that the same patent will match a standard later on. In other words, it is not sufficient for a patent to be novel and relevant to be included in a standard. If this statement is true, the release of a standard would have implications for stock market returns around the standard release date as it provides new information on firms and their proximity to the new technological frontier..

In Appendix C.1, we study how *Novelty* and *Proximity* relate to the patent's value as estimated in Kogan et al. (2017). We find that patents that are originally more novel and that –later on– will match better a new standard have higher economic value. It is now important to understand if this value –which in Kogan et al. (2017) is estimated at the patent grant date– already factors in future diffusion (through standards) or not and how *Novelty* and *Proximity* relate to stock market movements respectively around the date of patent grand and standard release.

Stock market reaction to innovation and standardization. If markets were able to perfectly predict which patent will be incorporated into a standard, based on its novelty, then the release of the standard and its content would not represent any new surprise. In this case, no variation in prices would be detected around the standard release date.

In the spirit of Kogan et al. (2017), here we test if this is the case by looking at firm-level excessive returns around both the patent grant date and the standard release date. In particular, we exploit our patent-standard dataset as follows. First, for each patent i belonging to firm f, we look at daily excessive returns (i.e. $r_{f(i),t} - r_t^{SP500}$) in a +/- 2-days window around the patent grant date t while controlling for firm fixed effect.

Formally, we estimate the following:

$$r_{f(i),t} - r_t^{SP500} = f_{(i)} + w_{t(i)} + \sum_{n=-5}^{N=5} \beta_n \mathbb{I}[day = t_i + n] + \epsilon_{f_{(i)},t} \tag{3}$$

where $f_{(i)}$ is the fixed effect of the firm owner of patent i and $w_{t(i)}$ is a time-window fixed effect centered around the publication of patent i (i.e. $t(i) - 5 \leqslant t(i) \leqslant t(i) + 5$). Figure 4(a) shows that –being the patent granted time 0– markets react positively in between the day of grant and the day after. The effect is not anticipated and lasts only one day.

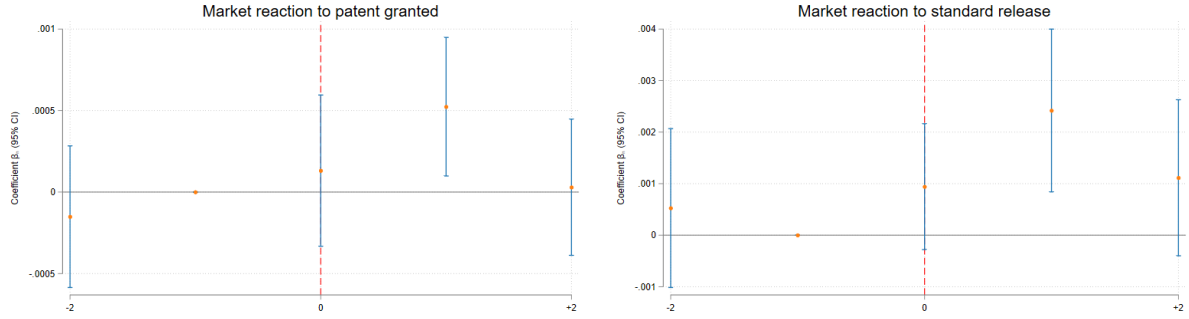
Second, for the subset of (potentially multiple) patents matching a standard s, i.e. those patents with *Proximity* > 0, we look at excessive returns in +/- 2-days window around the standard release date τ_s.[3] Similarly to equation (3), here we control for a firm fixed effect, a time-window fixed effect now centered around the publication of standard s (i.e. $\tau(s) - 5 \leqslant \tau(s) \leqslant \tau(s) + 5$) and also for the number of patents belonging to firm f and matching standard s in order to net out the potential effect of the patent portfolio size at the moment of the standard release.[4] Figure 4(b) shows that –being the standard released at time 0– markets react positively when a firm has one or more patent matching a standard. Also in this case, the effect is not anticipated and lasts only one day. This results corroborate the idea that –being the quality of the patent always observable– the release of a matching standard represents a new source of information unexpected by markets and not already priced in prior to the release of the standard.

Excessive returns at patent grant date. The above exercise measures the average excessive return as observed when a new patent is granted and when a patent matches a new standard. However, it does not take into account how much results depend on innovation quality and proximity to new standards. In light of this, we proceed by collecting all excessive returns observed in $t + 1$ and study how much they relate to our measure of *Novelty* and *Proximity*. In particular, in the case in which multiple patents are granted to the same firm on the same day, we take the mean value of the variable *Novelty* across those patents. As a patent can potentially match multiple standards in the future (see Table 1), we take the average of the variable *Proximity* across all future matching standards with positive scores (i.e. we eliminate the noise due to all matching patents with zero scores – see Table 1 and discussion in Section 3.1). Given this, we

[3] As explained in Bergeaud et al. (2026b), a first release of public information of the preliminary content of a standard is available already before the official publication of the standard in the SSOs gazette, when the first round of vote of scrutiny occurred. We back up from official documentation this date, which we use in this section to study stock market reaction to the release of first-time information on a new standard.

[4] Dropping this control does not change results.

Figure 4: STOCK MARKET REACTION



(a) Returns at patent grant date (b) Returns at standard publication date

Notes: Figure 4(a) and 4(b) plot the estimated coefficients of equation (3) when the event study is respectively the patent grant or the publication of a standard.

estimate the following:

$$r_{f(i),t+1} - r^{SP500}_{t+1} = f_{(i)} + \beta x_{f(i)} + \epsilon_{f_{(i)},t+1} \tag{4}$$

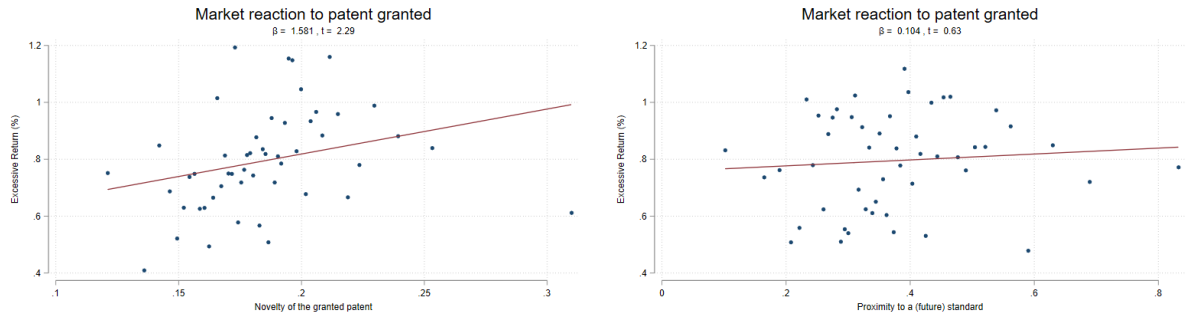
where $x_{f(i)}$ is either the value of $\mathtt{Novelty}$ of patent i belonging to firm f or the average value of $\mathtt{Proximity}$ across all future standards positively matched to patent i.

Figure 5(a) shows that there is a positive and significant relationship between excessive returns –as observed on the patent grant date t– and the novelty of the patent that has been granted. In words, the more the patented technology is novel and relevant, the higher is the excessive return observed on the stock market in the same day. In particular, for the average patent with level of *Novelty* $= 0.2$, the observed excessive return is 0.3 percentage points. On the other hand, in Figure 5(b) we show that there is no significant relationship between the average *Proximity* and the excessive returns observed when the patent is granted.

These results suggest that, at the moment of the patent release, markets factor in how much the new invented technology represents a novelty, i.e. a discontinuity with the past, and react proportionally. In contrast, they cannot foresee and immediately price in the potential of the new technology for large scale adoption and diffusion through standardization in the future.

Excessive returns at standard release date. Here, we repeat the same analysis but considering excessive returns observed at the standard release date $\tau + 1$ as dependent variable. This will clarify which component –*Novelty* vs. *Proximity*– is more important for markets at the moment a new standard is defined. To do so, we consider every single standard-patent match and estimate equation (4) augmented with a standard fixed effect θ_s, such that we can compare the novelty and proximity margins for patents that relate to the same standardized technology. Moreover, we add the following vector

Figure 5: EXCESSIVE RETURNS AT THE PATENT GRANT DATE: NOVELTY VS. PROXIMITY



(a) Returns vs. Novelty (b) Returns vs. Proximity

Notes: Figure 5(a) and 5(b) plot the estimated relationship of equation (4) when the explanatory variable is respectively *Novelty* and *Proximity*.

of controls $T'_{f(i),\tau}$: i) as some patents might have become fully obsolete no matter recent high patent-to-standard matching scores, we control for the age of the patent; ii) as a firm might have multiple patents matching the same standard due to the large patent portfolio size, we control also for the number of patents belonging to firm f and matching the standard s at the moment of its publication τ. Formally, we estimate the following:

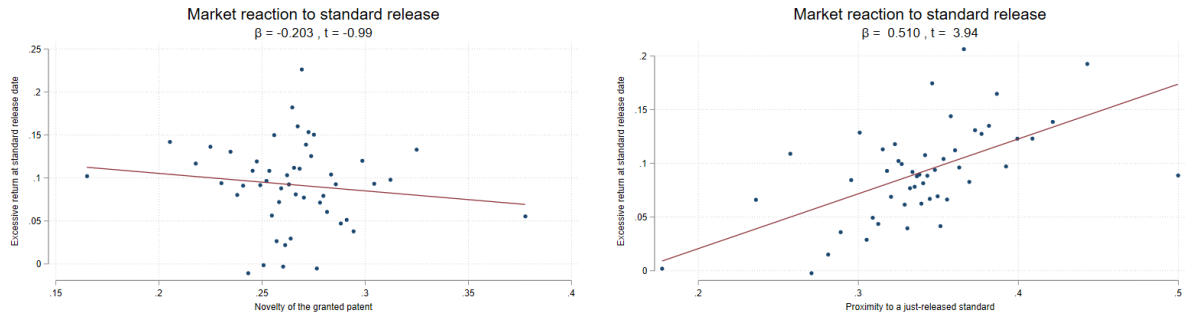
$$r_{f(i),\tau+1} - r^{SP500}_{\tau+1} = f_{(i)} + \theta_s + \beta x_{f(i)} + T'_{f(i),\tau}\gamma + \epsilon_{f_{(i)},\tau+1}. \tag{5}$$

Figure 6(a) shows that markets do not react at time $\tau > t$ proportionally to the original novelty of the patent. As quality is always observable, at time $\tau > t$, the novelty and relevance of past innovations is already priced in and markets do not react to this old information when a new matching standard is released. Conversely, as shown in Figure 6(b), excessive returns are larger the closer is the patent to the newly released standard. Markets, despite the observed quality of patents, react to the standard release proportionally to the degree of *Proximity*. In particular, for the average patent with *Proximity=0.38*, the observed excessive return on the market is 0.20 percentage points.

All in all, this evidence suggests that *Novelty* and *Proximity* convey two different pieces of information to markets. More importantly, at the patent grant date, markets price the new innovation based on its novelty. However, they cannot foresee and immediately price in whether a new patent is going to be included into a new standard and diffuse (through standardization) in the future. Conversely, when a new standard is released, markets react by pricing more those firms with patents closer to the new standard. At that moment, whether the patent was originally novel does not matter.

In conclusion, through this back-of-the envelope calculation, we can say that the diffusion margin contributes to 40% increase in the market value of the firm between the

Figure 6: EXCESSIVE RETURNS AT THE STANDARD PUBLICATION DATE: NOVELTY VS. PROXIMITY



(a) Returns vs. Novelty (b) Returns vs. Proximity

Notes: Figure 6(a) and 6(b) plot the estimated relationship of equation (5) when the explanatory variable is respectively *Novelty* and *Proximity*.

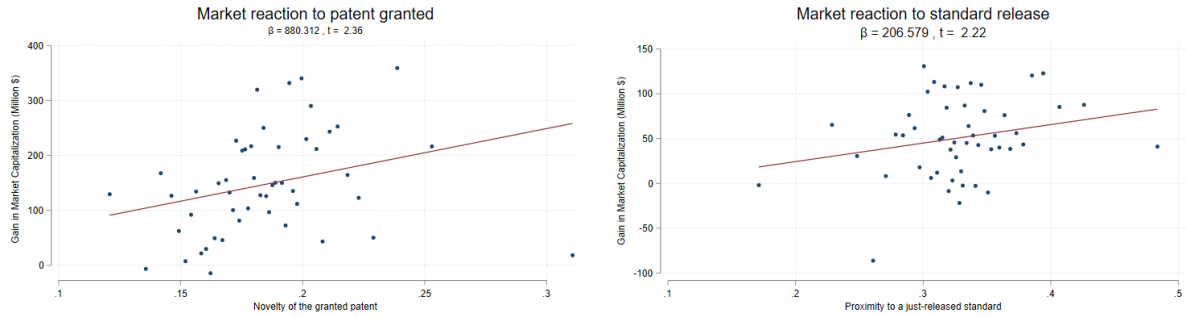
patent grant date and the release of the standard, *all else equal*.

These results are robust to a series of checks. As our measure of *proximity* to a standard can be exposed to measurement error, or capture other factors such as firm-level lobbying capacity and influence within SSOs (see Bekkers et al., 2011 and Farrell and Simcoe, 2012), we perform the following tests. In Appendix C.2, we leverage the data on SSOs membership from Baron and Pohlmann (2018) and exclude from our analysis all firms that were members of SSOs in the three years before the publication of a standard. Under this restriction, results hold. In words, firms that potentially had the influence and inside-information to build patent closer to the upcoming standard (prior to the standard release) are not those driving market reactions. This also proves that our measure effectively captures the proximity of patents to standards and it is not a by-product of other firm-level characteristics (e.g lobbying power and influence). To further test that our results are not driven by lobbying, we exclude all standards published by American SSOs, under the assumption that international SSOs are less exposed to unfair influence from American corporations (see Appendix C.3). Also in this case results hold true. Finally, to further corroborate the quality of our proximity measure, we proceed with a placebo test. In Appendix C.4, we associate every patent-to-standard match with a random score. Once endowed with this placebo, we estimate equation (5) and repeat the procedure 1000 times. The distribution of the the β-estimates have mean zero and is significantly different from the coefficient estimated with the true data. This allows us to conclude that the results of this section are not driven by noise and our proximity measure is meaningful.

3.2.3 Market value gains due to innovation and standardization

Previous results suggest that innovation and diffusion through technological standards can be considered two separate corporate events. Here, we want to quantify both

Figure 7: MARKET VALUE GAINS: NOVELTY VS. PROXIMITY



(a) Mkt. Gains vs. Novelty (b) Mkt. Gains vs. Proximity

Notes: Figure 7(a) and 6(b) plot the estimated relationship of equation (5) when the explanatory variable is respectively *Novelty* and *Proximity* and the dependent variable is the change in the market value of the firm.

margins in dollar terms by looking at the change in the market value of the firm[5]. This allows inferring the value of each patent and studying in which phase of its life-cycle the patent generates more value. To do so, we estimate equation (4) and (5) with the change in firm's market value –observed either at the release of a patent or at the release of a new standard– as dependent variable. Notice that controls remains as previously defined.

Figure 7(a) shows that there is a significant positive relationship between the market capital gain at the release of a new patent (at time t) and the degree of *Novelty* of the patent. In particular, for the mean patent with level of *Novelty* $= 0.2$, the market value gain is 175 million dollars.

Figure 7(b) shows that such significant and positive relationship exists also between the market value gain at the release of a new standard (at time $\tau > t$) and the degree of *Proximity* of the patent to the new standard. In particular, for the mean patent with level of *Proximity* $= 0.38$, the market value gain is 83 million dollars.

All in all, these results show that markets are more sensitive to the novelty of a new patent rather than its potential for diffusion. This reflects on prices, with the novelty of a patent being priced in more than its proximity to a new standard respectively at the moment of patent grant and standard release. From the back of the envelope calculation, we can say that –for the average patent– the entire process of innovation and diffusion contributes cumulatively to an increase in market value of 260 million dollars from the patent grant to its inclusion in a standard. The process of diffusion through standardization explains roughly 30% of the increase in total market value,

[5]The market value gain is defined as the change in market value as observed following the grant of a patent or the release of a new standard at the net of the systematic component due to market movements. For example, the gain for firm f following the release of patent i at time t is defined as $Mkt.\ Value\ Gain_{f(i),t+1} = (r_{f(i),t+1} - r^{SP500}_{t+1})Mkt.Value_{f,t}$.

ceteris paribus.

In Appendix C.5, we compare these estimates with those in the existing literature. In particular, we consider Kogan et al. (2017), which exploits the reaction of the stock market at the grant date to filter and extrapolate the true dollar value of a patent. Although we use a different methodology, we find a strong and significant correlation between our market value gains observed at the patent grant date and the true patent value estimated in their paper. Yet, our estimates are larger than those from Kogan et al. (2017) and the difference between the two is proportional to the *novelty* of each patent. This confirms our intuition: at the patent grant date, markets tend to over-valuate the novelty of new inventions beyond their true value (from Kogan et al., 2017). Conversely, consistent with our evidence from Section 3.2.2, the market value gains observed at the standard publication date do not correlate with the true patent value from Kogan et al. (2017). To sum up, markets are pricing different information respectively at the patent and standard release date.

4 Firm-level analysis

4.1 Firm-level data

Aggregated patent-level measures. To conduct our analysis at the firm level, we build firm-level counterparts of *Novelty* and *Proximity* at quarterly frequency. In particular, define as $\Gamma_{f,t}$ the set of patents granted to firm f in quarter t, then we can write:

$$\text{Tech.Novelty}_{f,t} = \frac{1}{|\Gamma_{f,t}|} \sum_{p \in \zeta_{f,t}} \text{Novelty}_{p,t}$$

as the average *Novelty* across all new patents granted to the firm. Intuitively, the higher is the variable *Tech.Novelty* the higher is the (average) relevance and novelty of the *flow* of new patents. For convenience, we scale this variable between zero and one.

The construction of the aggregate version of *Proximity* is not as straightforward. In fact, for a new standard (or multiple standards) published in quarter t, we need to consider the *stock* of patents issued up to that point in time and the extent to which they all match that standard. As discussed in Section 3.1 and described in Table 1, the average time for a patent to match a standard is 9 years. Moreover, within the firm, most patents do not match any standard or match it very poorly (*Proximity* ≈ 0). Therefore, averaging the value of *Proximity* across all matched patents and standards would give back only noise. In contrast, summing up scores from all matches allows us to better extract information on the extent to which the portfolio of patents of a firm is close to the new standard.

Yet, to do so, we also want to take into account two important things. First, firms

(in particular big conglomerates) tend to publish patents in different technological domains. Hence, we want to give more weight to those patent-standard matches that are at the core of the firm's research activity and technological field. To do so, we classify patents according to their International Patent Classification code (IPC) such that we can give more relevance to those matches in the technological field in which the firm has historically patented the most. In light of this, being J the set of all IPC classes, we define as ω_{f,j,t_0} the firm f's share of patents in the IPC class $j \in J$ measured in t_0, i.e. before 1980. Computing the weights in a pre-sample periods also reduces the problem of firm self-selection into a specific IPC, which firms anticipate will become important for a potential standard at some point in time.

Second, patents depreciate over time. For this reason, we introduce the discount factor $\zeta = (1 - \delta)$ that takes into account depreciation of the score generated from the match of patent i (granted at time $\underline{t}_i < t$) and standard s (published at time t). Following Madsen (2010), we set δ to match the annual rate of 20%. Depreciating scores will give less 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 aggregated measure limits the possibility of capturing ex-post standardization, i.e. the fact that a technology has entered into a standard only after full diffusion and adoption by all. 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.

Given all these ingredients, we can finally write the aggregate measure of *Proximity* as

$$\texttt{Tech.Proximity}_{f,t} = \sum_{j \in J} \omega_{f,j,t_0} \sum_{i \in j} \zeta^{(t-\underline{t}_p)} \texttt{Proximity}_{i,j,t}$$

where $\texttt{Proximity}_{i,j,t}$ is the score from the match of patent i with any standard issued in t and belonging to the IPC class j. This firm-level 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 $\texttt{Tech.Prox}_{f,t}$ the closer the firm's portfolio of patents to the newly released standard. Also in this case, we scale this variable between zero and one. As discussed in Bergeaud et al. (2026b), Tech.Proximity does not depend critically on the size of the patent portfolio or the number of standards matched by single patent. Ultimately, it depends mostly on the quality of the few high-scoring matches.

Balance-sheet data From Compustat, we consider the following variables of interest: the market value of the firm (built as the value of outstanding shares, and expressed in billions of USD), the book value of the firm (built as value of equity and short/long-term debt net of common preferred shares), leverage (as debt over the value of assets), the q-value of investments (built as the book value of liabilities plus the market value of

common equity divided by the value of assets), the age of the firm (expressed in quarters).[6] Using information on capital and employment, we build a firm-level measure of total factor productivity as a residual from the estimation of simple Cobb-Douglas production function for each firm as in Watt et al. (2023).[7] Finally, following De Loecker et al. (2020) we build a measure of firm-level markup.

Table 2: DESCRIPTIVE STATISTICS FOR FIRM-LEVEL DATA

	Mean	SD	p1	p5	p25	p50	p75	p95	p99	N
(A) Novelty and Proximity										
Tech.Novelty (%)	3.84	9.52	0.00	0.00	0.00	0.00	2.30	22.56	48.21	22,212
$\mathbb{I}$[Tech.Nov > 0]	0.63	0.48	0.00	0.00	0.00	1.00	1.00	1.00	1.00	22,212
Tech.Proximity (%)	0.48	2.32	0.00	0.00	0.00	0.00	0.19	1.99	8.15	22,212
$\mathbb{I}$[Tech.Prox > 0]	0.49	0.50	0.00	0.00	0.00	0.00	1.00	1.00	1.00	22,212
(B) Firm Value and Characteristics										
Market value	8.78	26.80	0.00	0.02	0.19	1.28	5.45	40.80	132.64	22,212
Book value	4.44	19.15	0.00	0.01	0.14	0.87	3.27	16.64	45.47	22,212
Leverage	0.19	0.15	0.00	0.00	0.07	0.17	0.27	0.44	0.64	22,212
Tobin's Q	1.88	1.59	0.74	0.89	1.17	1.48	2.06	4.06	7.52	22,212
Age (quarters)	101.07	48.99	21.00	22.00	63.00	111.00	138.00	171.00	181.00	22,212
Productivity	0.00	0.18	-0.54	-0.26	-0.07	0.01	0.09	0.25	0.43	22,212
Markup	1.50	0.69	0.87	0.98	1.12	1.27	1.61	2.76	4.66	22,212

Notes: This table reports descriptive statistics at the firm level for the variable *Tech.Novelty* and *Tech.Proximity* along with balance-sheet data on the market value and book value of the firm, age, Tobin's Q value of investment, productivity and markup. See Section 4.1 fo more details on data construction and variables definition.

As shown in panel A of Table 2, the mean novelty of the flow of newly granted patents is 4% and 63% of firm-quarter observations have a positive value of *Tech.Novelty*. The mean proximity of the stock of patents to a standard is equal to 0.48%. In our sample, 49% of firms have a positive proximity value. As from panel B, the average market value is 8.8 billion dollars while the average book value of the firm is 4.4 billion dollars. The average firm has a leverage equal to 19%, Q-value of investment equal to 1.9 and 25 years of age. The average productivity gain/loss is 0 with standard deviation equal to 0.18, and the average markup is 1.50.

[6] The market and book value of the firm are deflated at 1985 prices.

[7] For each firm i in the sample, we estimate the following : $\log(\text{Sales}_{f,t}/\text{Assets}_{f,t}) = \alpha_i + \beta_1 \log(\text{Capital}_{f,t}/\text{Assets}_{f,t}) + \beta_2 \log(\text{Employment}_{f,t}/\text{Assets}_{f,t}) + \varepsilon_{f,t}$. As Compustat provides employment data only at yearly frequency, we interpolate this variable to transform it at quarterly frequency. The residual $\varepsilon_{f,t}$ is the measure of firm-level of total factor productivity gain ($\text{productivity}_{f,t}$) that we consider in our empirical analysis.

4.2 Firm-level analysis and results

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

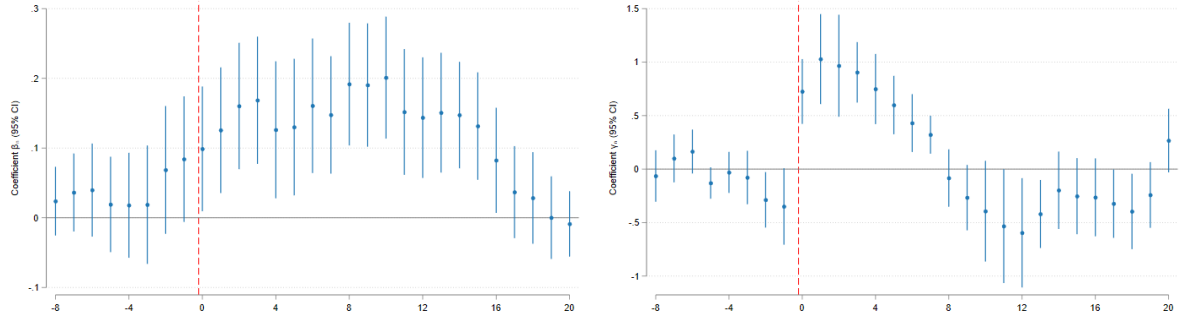
In light of this argument, our generic model is described in equation (6):

$$\begin{aligned} \log(Y)_{f,t} = &\sum_{n=-8}^{N=T} \beta_n \textit{Tech.Novelty}_{f,t-n} + \sum_{n=-8}^{N=T} \gamma_n \textit{Tech.Proximity}_{f,t-n} \\ &+ \alpha_{f,t} + \phi_{s(f),t} + X'_{f,t-1}\eta + \varepsilon_{f,t} \end{aligned} \tag{6}$$

where $\alpha_{f,t}$ and $\phi_{s(f),t}$ are respectively the firm and NAICS 3-digit industry fixed effects interacted with year and quarter time dummies. This controls for any time effect that might differ across firms (e.g. change of management, seasonality in sales, M&A, etc.) industries (e.g. because of sector-specific demand variation, seasonality, changes in legislation at the industry-level, momentum, etc.). Finally, following Chan et al. (1990), X is a vector of control variables including the age of the firm and its square, the lag of leverage, q-value of investment. $\varepsilon_{f,t}$ is the error term, which we assume to be normally distributed (conditional on all our covariates) and to be independent across different i.

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

Figure 8: INNOVATION, STANDARDIZATION AND THE MARKET VALUE OF THE FIRM



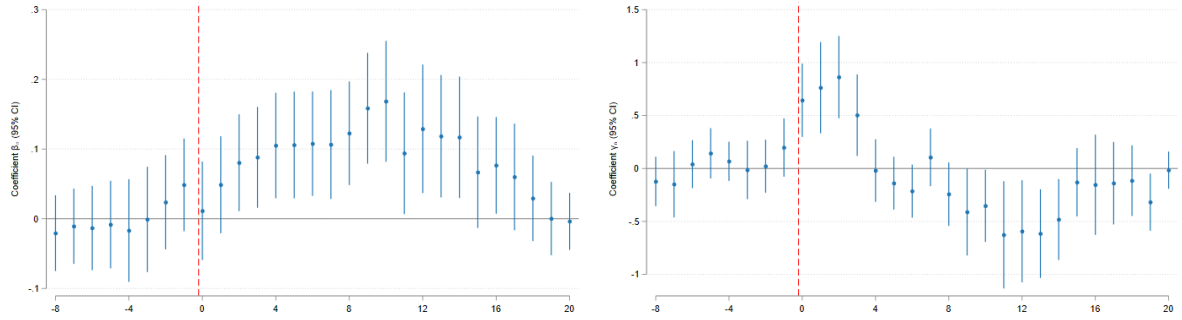
(a) Novelty (b) Proximity

Notes: Figure 8(a) and 8(b) plot the estimated coefficients β_n and γ_n of equation (6). The dependent variable is the log-level of market value of the firm. In both figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are clustered at the firm-level. The red-dashed line indicates respectively the grant date of a patent and the publication date of the standard.

Effect on the market value of the firm. First, we consider the market value of the firm as dependent variable (i.e. $\log(Y)$). Thus, we estimate model (6) with $T = 20$, i.e. 20 lags, and by clustering errors at the firm level. The figure below plots the estimated β_n and γ_n along with 95% confidence intervals. Consider first the contribution of innovation quality (β_n). As shown in Figure 8(a), until the quarter of release of the new patents, no pre-trend is detected: the market value of innovating and non-innovating firms is not significantly different. Conversely, the difference starts to be significant from t onwards. In particular, the more the average new patent granted at t is innovative and relevant, i.e. the higher is *Tech.Novelty*, the bigger is the increase in the firm's value (relative to non-patenting firms). This effect is persistent over time and dies out after roughly 4 years. This first result corroborates previous evidence in the literature (Hall et al., 2005, Pakes, 1985, Belenzon and Patacconi, 2013) showing the importance of innovation activity and quality of R&D output for the value of the firm, beyond the (short-run) value generated through stock price movement at the patent grant date.

When considering the effect of standardization, we obtain similar but less persistent dynamics. As shown in Figure 8(b), also in this case no pre-trend is detected. When a new standard is published at $t = 0$, firms that align the most with it –i.e. firms that already own technologies now included in the new standard– benefit from an immediate increase in firm value. Such increase is more temporary (roughly two years). This dynamic is coherent with Bergeaud et al. (2026b), which show that firms owning technologies included in a new standard benefit from a competitive advantage that translates into a temporary increase in sales. In fact, firms closer to the standard generate more cashflow and revenues since they are able to immediately deploy, scale and market their technology while competitors need to catch-up. Over a longer horizon, as firms far away from the frontier adapt (see Section 3.2.1), the competitive advantage dies out or even temporarily diminishes.

Figure 9: INNOVATION, STANDARDIZATION AND THE BOOK VALUE OF THE FIRM



(a) Novelty (b) Proximity

Notes: Figure 9(a) and 9(b) plot the estimated coefficients β_n and γ_n of equation (6). The dependent variable is the log-level of the book value of the firm. In both figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are clustered at the firm-level. The red-dashed line indicates respectively the grant date of a patent and the publication date of the standard.

Effect on the book value of the firm. If the market value is mostly a forward-looking measure of future cash-flows, growth opportunities and value of intangibles, the book value of the firm is a backward-looking measure of realized growth through earnings reinvested in the firm. In light of this, here we study how innovation and diffusion affect the size of the balance-sheet in order to comprehend if the firm's increase in value is accompanied also by effective (accounting) growth.

Hence, we use the log of the firm's book value as dependent variable in model (6). As shown in Figure 9(a), firms that are able to produce novel and relevant technologies see their book value increase more. As before, the effect is persistent and dies out only after 4 years. Figure 9(b) shows that firms whose patents are more aligned with the new standard benefit from a larger increase in book value. Differently from the results on the market value, here the effect lasts one year only.

In light of this evidence, we conclude that, in the race between innovation and standardization, both margins contribute significantly to firm market value and growth, as measured by market and balance-sheet valuation. For both market and book value, the innovation margin is more important: the development of a novel patent has a larger and more persistent effect on the firm's value than its inclusion into a standard. In fact, when the same patent is subsequently incorporated into a new standard, the resulting process of standardization and diffusion generates a smaller and less persistent additional increase in value. This happens because, as standardized technologies diffuse throughout the industry, lagging firms are able to catch up, gradually eroding the competitive advantage initially enjoyed by technological leaders. Consequently, the benefits of standardization are attenuated by the very diffusion process that standards are designed to promote (see Bergeaud et al., 2026b).

Finally, when comparing the results from the two estimations, we find that the point estimates for both the innovations and the diffusion margins are larger when looking

at the market value of the firm. In other words, more value is generated through higher market expectations on future earnings and gains from intellectual property rights (see Eisfeldt and Papanikolaou, 2013 and Gerakos and Linnainmaa, 2018). This is particularly evident when looking at the effect of standardization, which is larger and more persistent for the market value of the firm. In fact, with the release of a new standard, markets recognize which firms can immediately deploy and scale and market their invention with higher commercial prospects.

Also these results are robust to the same list of checks conducted for our patent-level analysis of Section 3.2.2. In particular, in Appendix D.1-D.4, we show that results hold true when controlling for firm-level SSOs membership, for the size of the patent portfolio and strategic patenting activity (i.e. for abnormal publication of patents in the year prior to the publication of the standard), when the variable *Tech.Proximity* is built excluding American SSOs, or it is built considering only the best matches in the firm-level aggregation. Moreover, results are robust to a placebo exercise: when aggregating random scores at the firm level, no result is detected (see Appendix D.5). Finally, in Appendix D.6 we show that, conditional on fixed effects, firms are not significantly different in observables in the year prior to the publication of a patent and/or a standard.

4.3 The long-run contribution of innovation and standardization

In this section, we perform a back-of-the-envelope calculation of the long-run cumulative effects of innovation and standardization.

To this end, we first estimate model (6) using the year-on-year percentage change as dependent variable, i.e. $\Delta \log(Y)$, and over a longer horizon ($T = 60$). We then store all estimated coefficients β_n and γ_n, evaluated at the mean level of the explanatory variable Tech.Novelty and Tech.Proximity.

Second, we cumulate the innovation and diffusion margin while taking into account the conversion rate of patents into standards. In fact, as reported in Table 1, the technology disclosed in a patent is, on average, incorporated into a standard approximately 9 years (or 36 quarters) after the patent grant date. Therefore, to properly assess the cumulative effect, it is necessary to account for the timing at which this effect materializes across firms and over time. In other words, we explicitly take into consideration the empirical distribution of lags between the patent grant date and the subsequent publication of the relevant standard.

In detail, define λ_t as the average probability across firms that a patent granted at time t becomes a standard in the same period, i.e. the lag between innovation and standardization is zero. Then, for this group of firms that see immediate conversion of patents into standard, the total effect of releasing a patent at time t is equal to $\beta_t + \lambda_t * \gamma_t$, i.e. the increase in value due to innovation activity summed to the (probability

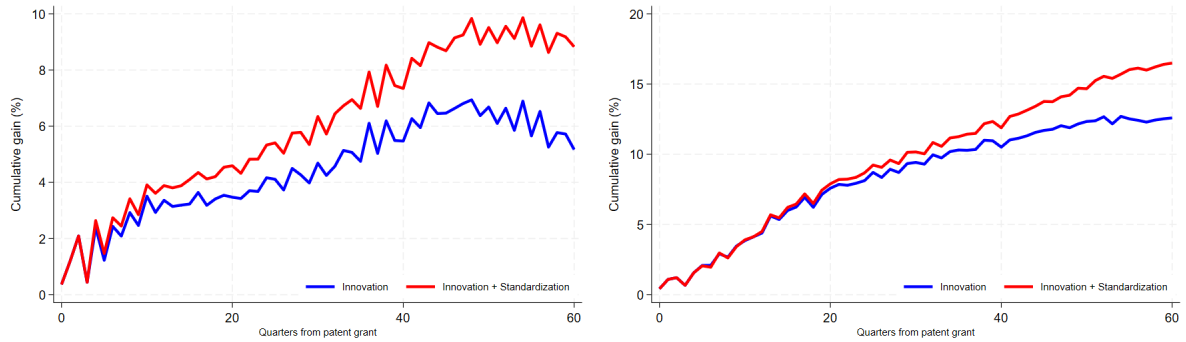
weighted) premium if that innovation is included in a standard in the same period. In $t+1$ there is a probability λ_{t+1} that a firm see at least one of their patents granted at time t to be included in a standard issued in time $t+1$, i.e. the lag between innovation and standardization is now one period for this group of firms. Then the total effect of releasing a patent at t, cumulated over the first two periods, is $\beta_t + \beta_{t+1} + \lambda_t * (\gamma_t + \gamma_{t+1}) + \lambda_{t+1} * \gamma_t$. In words, on top of the cumulative effect of innovation ($\beta_t + \beta_{t+1}$), we consider the effect standardization for that group of firms that have seen their patents becoming standard already at t ($\lambda_t * (\gamma_t + \gamma_{t+1})$), plus the group of firms that have seen their patents becoming a standard at $t+1$ ($\lambda_{t+1} * \gamma_t$). Similarly, the total effect at time $t+2$ is $\beta_t + \beta_{t+1} + \beta_{t+2} + \lambda_t * (\gamma_t + \gamma_{t+1} + \gamma_{t+2}) + \lambda_{t+1} * (\gamma_t + \gamma_{t+1}) + \lambda_{t+2} * (\gamma_t)$. We proceed recursively to build the cumulative effect of innovation and the joint cumulative effect of innovation and standardization over time up to T periods after the patent grant date.

Figure 10(a) shows results when the dependent variable is the growth rate of the market value of the firm. Relative to firms that do not innovate, firms being granted patents of average relevance and novelty at time $t = 0$ see their market value increasing cumulatively up to 6% around 11 years after patent grant. Thereafter, the market value deteriorates by almost 1 percentage point such that the overall increase in value in the long run is 5%. This is not true for firms whose patents averagely match new standards. Taking into account of the probability of inclusion of patents into standards, we find that those firms whose technologies diffuse through standardization see their market value increasing up to 9% in the long run. The divergence between the two effects is more marked around the 40^{th} quarter following the patent grant. This reflects well the fact that –as discussed in Section 3.1– the average patent is included into a standard 9 years after patent grant.

Figure 10(b) shows results when the dependent variable is the growth rate of the book value of the firm. Relative to firms that do not innovate, firms that have been granted a patent of average novelty and relevance see their value increase up to 10% in the first 60 quarters following the patent grant date. thereafter, the dynamic plateaus such that the cumulative gain reaches 12% in the long run. Conversely, when considering the cumulative joint effect of innovation and diffusion through standardization, we find that firms whose patents align averagely with a new standard experience an increase in value bigger than those that innovate but do not see their patents included into a standard. In particular, firms whose patents are included in a standard –differently from those who do not– see their value increasing up to 17% in the long run. Also in this case, the divergence between the two effects is more marked roughly ten years after the patent grant.

All in all, these results support the idea that firms whose patents are incorporated into a standard follow a different trajectory with respect to firms whose technologies are not diffused through standardization. Specifically, when a firm's technology is neither

Figure 10: LONG-RUN CONTRIBUTION OF INNOVATION AND STANDARDIZATION TO THE MARKET AND BOOK VALUE OF THE FIRM



(a) Market Value (b) Book Value

Notes: Figure 10(a) and 10(b) plot the (weighted) cumulative sum of the estimated coefficients β_n and γ_n of equation (6) when the dependent variable is respectively the book and market value of the firm.

adopted nor disseminated at the industry level through standards, the value generated by innovation tends either to decline over time (in terms of market value) or to plateau (in terms of book value). By contrast, firms whose innovations are embedded in industry standards not only experience a greater increase in value, but are also able to sustain these gains over time.

Overall, the contribution of diffusion to the total long-run increase in the firm's value is roughly 40% when looking at the market value and 30% when looking at the book value.

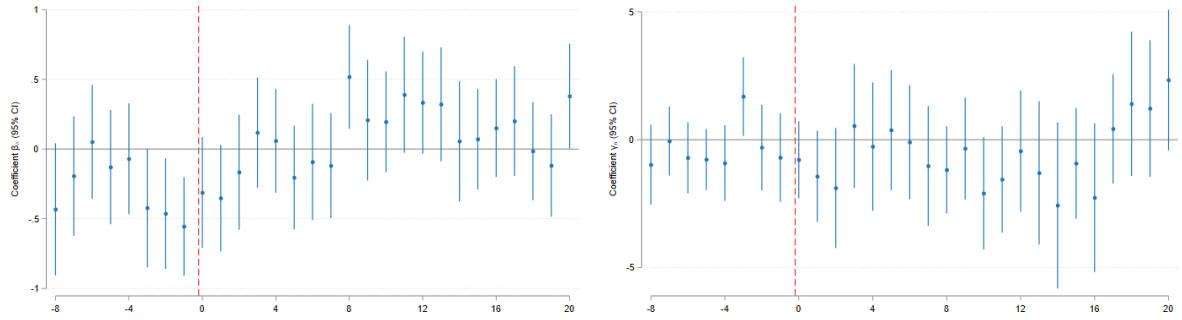
4.4 Innovation vs. Standardization: productivity gains vs. rent extraction

Overall, Sections 3.2-4.3 provide evidence on the effects of innovation and diffusion of novel technologies –through standard-setting– on firm value. The next step is to clarify through which mechanisms these two margins contribute to the value of the firm.

There is a substantial body of evidence linking innovation activity and R&D expenditure to firm-level productivity (see, among others, Watt et al. (2023) and Bartz-Zuccala et al. (2018)). On the other hand, the literature on innovation and competition (see, among others, Aghion et al. (2005)) suggests that when a firm attains a technological lead, market competition temporarily declines as the firm effectively becomes a (quasi-)monopolist over the new invention. As long as knowledge spillovers and subsequent R&D investments do not enable competitors to catch up, leading firms are able to extract rents from the market.

In light of this, in this section we examine which margin –innovation or diffusion– is primarily associated with productivity gains and which is instead linked to rent extraction.

Figure 11: PRODUCTIVITY GAINS FROM INNOVATION AND STANDARDIZATION



(a) Novelty (b) Proximity

Notes: Figure 11(a) and 11(b) plot the estimated coefficients β_n and γ_n of equation (6). The dependent variable is firm-level productivity gain. In both figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are clustered at the firm-level. The red-dashed line indicates respectively the grant date of a patent and the publication date of the standard.

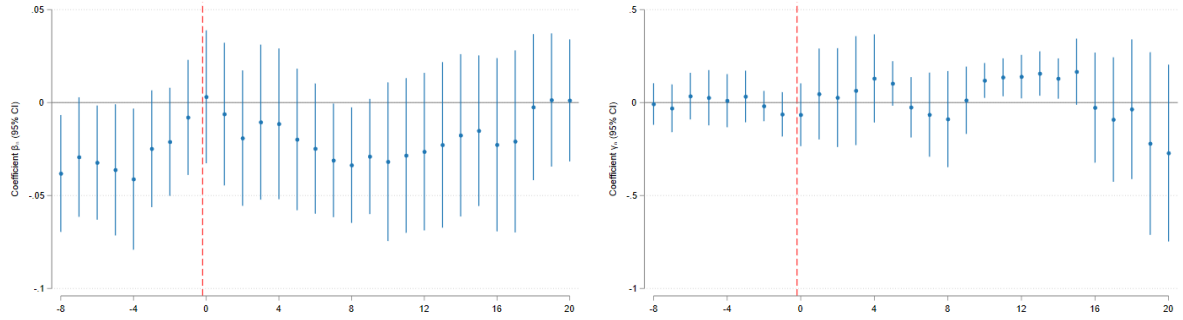
Productivity gains. Here, we use the $\log(100 \times \text{Productivity}_{f,t})$ as dependent variable in model (6). Figure 11(a) shows results for the dynamic effect of the release of a patent. Roughly 2 years after their grant, firms releasing patents of higher novelty and relevance have a stronger increase in efficiency in production. Such gains appear to persist for more than a year. Conversely, Figure 11(b) shows that having a patent included into a new standard does not lead to productivity gains. This result is consistent with the idea that producing a good technology or developing a high quality procedure/practice in production increases the productivity of the firm. However, the diffusion of such technology (through standards) does not provide any further productivity gain for the firm.

Rent extraction. In light of this, we now consider how the margin of innovation and diffusion affects the ability of the firm to extract rent from the market. Hence, we use $\log(\text{Markup})_{f,t}$ as dependent variable in model (6).

Figure 12 show results. The markup of the firm does not increase for firms releasing a new and promising technology (see figure 12(a)). This suggests that it is not sufficient for a firm to innovate well in order to distort competition and extract rent from the market. Conversely, when a firm sees its patents being included into a new standard, then distortions in market competition occur. In fact, although temporarily, the markup significantly increases for those firms whose patents' features are picked by a standard organization (see figure 12(b)).

As discussed in Bergeaud et al. (2026b), firms holding patents that are closer to a newly released standard enjoy a temporary competitive advantage relative to other market participants, which translates into a short-run increase in sales and market share. This advantage arises because these frontier firms already possess the relevant technological know-how embedded in their patent portfolios, enabling them to comply with

Figure 12: RENT EXTRACTION FROM INNOVATION AND STANDARDIZATION



(a) Novelty (b) Proximity

Notes: Figure 12(a) and 12(b) plot the estimated coefficients β_n and γ_n of equation (6). The dependent variable is the the firm-level markup. In both figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are clustered at the firm-level. The red-dashed line indicates respectively the grant date of a patent and the publication date of the standard.

the new standard and adjust production accordingly. By contrast, firms that are farther from the technological frontier defined by the standard must reorganize their production processes and acquire the necessary knowledge through additional R&D investments in order to realign themselves with the new technological requirements. This adjustment process is costly and time-consuming, thereby delaying their ability to compete effectively under the new standard. As a result, standardization creates a temporary window of rent extraction for technologically leading firms.

5 Conclusion

Technological innovation and diffusion play distinct and important roles in shaping firm value over time. This paper disentangles these two margins and examines how each contributes to firm value in the long run.

Separating innovation from diffusion is empirically challenging, given that both processes are inherently endogenous. To address this issue, we exploit a specific mechanism of technology diffusion at the industry level: technology standardization. In fact, technology standards (e.g. 5G) are defined by national and international standard organizations to select and promote the widespread adoption of the most efficient technologies and practices. In this context, we conduct a semantic analysis of standards documents and firms' patents. In particular, we construct a measure capturing the extent to which the technologies developed by a firm are incorporated into a new standard, based on the textual similarity between standards and patent abstracts. This measure, combined with indicators of patent novelty and technological relevance from Kelly et al. (2021), as well as detailed information on the timing of patent and standard publication, allows us to separately identify the effects of innovation and diffusion through standardization on firm value in the short and long run.

First, we provide patent-level evidence that neither firms nor financial markets can anticipate which patents are more likely to be included into a standard. Both firms and markets react only once a new standard is published and its technical features revealed. In particular, it is only from the moment of the standard's publication onwards that firms start producing patents and technologies that resemble more those embedded in the new standard. Similarly, it is only at the standard publication date that financial markets revise upward the valuation of those few firms that already hold patents closely aligned to the new standard, reflecting an ex-post recognition of their strategic positioning. Overall, we find that firm's market valuation increases by 0.3% when an (average) novel patent is granted. The inclusion of that patent into a standard later on leads to a further 0.2% increase in value. In other words, these results suggest that the diffusion process through standardization account for 40% of the total increase in market value as observed around the patent grant and standard publication dates.

Second, through this empirical setup, we provide firm-level evidence that innovation and diffusion through standardization contribute also to the firm's value in the long run and in different ways. If, on one hand, good innovation has a persistent effect, on the other hand diffusion (through the process of standardization) has only a temporary effect on the market and book value of the firm. Overall, for average patent, the cumulative contribution of the diffusion margin to the total long-run increase in the firm's value is 40% when looking at the market value, and 30% when looking at the book value.

Finally, we investigate the channels through which the innovation and diffusion margins affect the value of the firm. By studying the evolution of firm-level productivity and markups, we show that the increase in the value of the firm explained by the innovation margin is due to persistent productivity gains that the firm gets from the production of a new promising technology or production practice. On the other hand, the increase in the value explained by the diffusion margin –through the process of standardization– is due to rent extraction. In fact, as explained in Bergeaud et al. (2026b), firms that see their technology included in a standard have an immediate competitive advantage relative to competitors: they already have the know-how to comply immediately with the standard while all others need time to adjust.

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FOR ONLINE PUBLICATION: APPENDIX

A Data

A.1 Standards data

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

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

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

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

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

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

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

Keywords are cleaned and processed as described in B below.

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

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

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

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

B Matching

B.1 Matching procedure

B.1.1 Brief outline of the matching procedure

Our goal is to find the patents that are the "closest" to a given standard. Our approach relies on the set of keywords associated with a standard, which we take to be a sufficient information set to describe the standard, and on the abstract of patents. More specifically, for each standard, we scan our patent database and give a score for each patent that reflects how relevant these standard's keywords are to describe the patent's abstract. One of the main challenge with this type of large scale data mining approach is to design a method that is suitable for big data (there are about 0.65 million standards and 7.5 million US patents in our dataset). We briefly present our approach below.

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

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

We process these keywords as follows.

1. **Stemming and cleaning keywords**: this first step consists in "normalizing" the set of keywords contained in each standard by removing upper-case letter, punctuation and "stop-words" (*the*, *at*, *from* etc...). We then keep only the stem of each word.[8]

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

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

as groups of size k, with $k \leqslant 3$. The rationale from considering group of words can be illustrated with the example of a standard containing "air conditionning" as one of its keywords. If we do not consider k-grams in addition to single stems, then we would be screening the patent database for the stems *air* and *condition*, which are clearly irrelevant in that case. Thus, at the end of this procedure, we can associate for each standard j a set $\mathcal{A}(j)$ of 1-grams, 2-grams and 3-grams taken from its keywords.[9]

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

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

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

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

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

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

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

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

This procedure will allow as to define the set of keywords in the abstract of patent i ($\mathcal{B}(i)$). We proceed to the same cleaning and stemming procedure as for standards' keywords such that we can build, for every keyword w_k, the inverse document frequency in the patent domain $\text{IDF}(w_k^B)$. Note that contrary to other studies that have used semantic analysis on patents' abstract (see e.g. Bergeaud et al., 2017 or more generally regarding patents Adams, 2010), we are not doing anything to select words based on their grammatical functions in the abstract. This is because the number of standards' keywords is limited and there is no need to reduce the size of the patents' abstracts to improve the performance of the algorithm.

B.1.2 Measuring proximity

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

- We want to give more weight to keywords that have a high IDF since they are more likely to be useful in describing the specificity of a given standard.
- We want to favor keywords in the patent domain that are repeated several times in the abstract of the patent. This allows to better weight the specificity of a k-gram to a certain patent. Therefore, by integrating the term frequency of each k-gram (TF) in the proximity measure, the score increases the relevance of that keyword in describing the patent.

Once endowed with all these elements, we follow the literature (e.g., Seegmiller et al., 2023, Kelly et al., 2021) and define a measure of bilateral proximity between each standard s and patent i based on cosine similarity. As also described in Section 3.1, we define

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

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

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

where $\text{IDF}(w_k^A)$ and $\text{IDF}(w_k^B)$ denote the inverse document frequency of keyword w_k across the entire corpus of standards and patents respectively, and $\text{TF}(w_k)$ is the term frequency of w_k within the patent abstract.

B.1.3 Implementation in practice

The size of the databases poses technical difficulties. Because there are more than 7.5 million US priority patents and about 0.65 million unique standard documents, we are faced with over 4.9×10^{12} possible matches. We proceed as follows. We first extract all the cleaned and stemmed k-grams from the standards keywords and store these as a dictionary with which all patent abstracts are compared in the next step. When extracting k-grams from the patent abstract, we do not store any k-grams that do not appear in our dictionary of admissible keywords obtained from the standards keywords. We do so for two reasons. First, as the goal of the keyword extraction from patent abstracts is to match those to standard keywords, we do not need to store redundant keywords as they do not match with anything that is in our standards database. Second, the keyword extraction proceeds in forming k-grams from a continuous text that has been stemmed, thus building a large number of k-grams void of sense. For example, from the sentence “The authentication procedure allows for personal data protection.” which becomes “authenticat proced allow personal data protect” after stemming, the following 3-grams are extracted from the text: “authenticat proced allow”, "proced allow personal", "allow personal data", "personal data protect" as well as the corresponding 2-grams. Only the 3-gram "personal data protect" as well as the 2-grams “authenticat proced”, “personal data” and “data protect” are probably meaningful, which is why the use of a pre-defined dictionary as a benchmark is warranted.

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

B.2 Matching of ICS and IPC classes

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

Table B.1: ICS-IPC CONCORDANCE

ICS	ICS description	IPC	IPC description
1	Generalities. Terminology. Standardization. Documentation	E04	Building
3	Services. Company Organization, Management And Quality. Administration. Transport. Sociology	G06	Computing; calculating; counting
7	Mathematics. Natural Sciences	C12	Biochemistry; beer; spirits; wine; vinegar; microbiology; enzymology; mutation or genetic engineering
11	Health Care Technology	A61	Medical or veterinary science; hygiene
13	Environment. Health Protection. Safety	C02	Treatment of water, waste water, sewage, or sludge
17	Metrology And Measurement. Physical Phenomena	G01	Measuring; testing
19	Testing	G01	Measuring; testing
21	Mechanical Systems And Components For General Use	F16	Engineering elements or units; general measures for producing and maintaining effective functioning of machines or installations; thermal insulation in general
23	Fluid Systems And Components For General Use	F16	Engineering elements or units; general measures for producing and maintaining effective functioning of machines or installations; thermal insulation in general
25	Manufacturing Engineering	B23	Machine tools; metal-working not otherwise provided for
27	Energy And Heat Transfer Engineering	G21	Nuclear physics; nuclear engineering
29	Electrical Engineering	H01	Basic electric elements
31	Electronics	H01	Basic electric elements
33	Telecommunications. Audio And Video Engineering	H04	Electric communication technique
35	Information Technology. Office Machines	H04	Electric communication technique
37	Image Technology	G03	Photography; cinematography; analogous techniques using waves other than optical waves; electrography; holography
39	Precision Mechanics. Jewellery	A44	Haberdashery; jewellery
43	Road Vehicles Engineering	B60	Vehicles in general
45	Railway Engineering	B64	Aircraft; aviation; cosmonautics
47	Shipbuilding And Marine Structures	B63	Ships or other waterborne vessels; related equipment
49	Aircraft And Space Vehicle Engineering	B64	Aircraft; aviation; cosmonautics
53	Materials Handling Equipment	B66	Hoisting; lifting; hauling
55	Packaging And Distribution Of Goods	B65	Conveying; packing; storing; handling thin or filamentary material
59	Textile And Leather Technology	D01	Natural or artificial threads or fibres; spinning
61	Clothing Industry	A44	Haberdashery; jewellery
65	Agriculture	A01	Agriculture; forestry; animal husbandry; hunting; trapping; fishing

Continuation of Table B.1

ICS	ICS description	IPC	IPC description
67	Food Technology	A23	Foods or foodstuffs; their treatment, not covered by other classes
71	Chemical Technology	F42	Ammunition; blasting
73	Mining And Minerals	E21	Earth or rock drilling; mining
75	Petroleum And Related Technologies	C07	Organic chemistry
77	Metallurgy	C23	Coating metallic material; coating material with metallic material; chemical surface treatment; diffusion treatment of metallic material; coating by vacuum evaporation, by sputtering, by ion implantation or by chemical vapour deposition, in general; inhib
79	Wood Technology	B27	Working or preserving wood or similar material; nailing or stapling machines in general
81	Glass And Ceramics Industries	C03	Glass; mineral or slag wool
83	Rubber And Plastic Industries	C08	Organic macromolecular compounds; their preparation or chemical working-up; compositions based thereon
85	Paper Technology	D21	Paper-making; production of cellulose
87	Paint And Colour Industries	B05	Spraying or atomising in general; applying liquids or other fluent materials to surfaces, in general
91	Construction Materials And Building	E04	Building
93	Civil Engineering	E02	Hydraulic engineering; foundations; soil-shifting
95	Military Engineering	F41	Weapons
97	Domestic And Commercial Equipment. Entertainment. Sports	A63	Sports; games; amusements

B.3 An example of matching patents to a standard

In this section, we discuss an example of the patent-standard matching. We consider standard DD238, published on the 15th of October 1996 by the British Standards Institution (BSI) and titled "Fieldbus - Specification for data link services subset". Due to property rights covering official documents, we cannot disclose here the abstract of the standard but we report below a brief description of the technology described by this standard as it falls under a broader group of technology called "open system interconnection (OSI) data link layer". As from Wikipedia: "[...] This layer is the protocol layer that transfers data between nodes on a network segment across the physical layer. The data link layer provides the functional and procedural means to transfer data between network entities and may also provide the means to detect and possibly correct errors that can occur in the physical layer. The data link layer is concerned with local delivery of frames between nodes on the same level of the network[...]".

As reported in Perinorm, the keywords associated with standard DD238 are the following:

communication networks; computer networks; bus networks; open systems interconnection; data link layer (osi); data transmission; data transfer; quality; interfaces (data processing) network management ; osi.

We consider two patents, both issued before the standard and owned by two different companies.

- **Patent A - owner: IBM; patent code: US-5241682; date: 1993-08-31**

  Title - Border node having routing and functional capability in a first network and only local address capability in a second network

  Abstract - A method and apparatus for interconnecting multiple data processing networks, each data processing network including: multiple network nodes having routing and functional capability within a data processing network; and, multiple endpoint nodes, each including only local address capability. Each network node may be connected to multiple endpoint nodes and other network nodes; however, connection is only permitted to network nodes within the same data processing network. A border node is established for interconnection between two data processing networks. The border node includes a network node interface having routing and functional capability within a first data processing network and an endpoint node interface having local address capability. When interconnected between the first data processing network and a network node within a second data processing network, the border node emulates a network node within the first data processing network while appearing as an endpoint node within the second data processing network, permitting full connectivity between the two networks. The border node then maintains routing information for communication between the two data processing networks in two segments. A first segment details the route between the first data processing network and the border node while a second segment details the route between the border node and a node within the second data processing network.

- **Patent B - owner: Atmel Corp; patent code: US-5218240-A; date: 1993-06-08**

  Title - Programmable logic cell and array with bus repeaters

  Abstract - A programmable logic array comprising cells and a bus network in which the cells are arranged in a two-dimensional matrix of rows and columns and are interconnected by the bus network. The cells are also interconnected by a two-dimensional array of direct connections between a cell and its four nearest neighbors, one to its left (or to the West), one to its right (or to the East), one above it (or to the North) and one below it (or to the South). Each cell comprises eight inputs, eight outputs, means for multiplexing the eight inputs onto two leads and logic means that operate in response to the signals on the two leads to produce output signals which are applied to the eight outputs. The bus network comprises a local, a turning and an express bus for each row and column of the array and repeater means for partitioning said buses of a given row or column so as to form bus segments. The bus network provides for transfer of data to the cells of the array without using the cells as individual wires.

Following the definition of *Proximity* from B.1.2, the computed score from patent A is bigger than the score from patent B. Despite the fact that both patents describe a technology that aims at facilitating the transfer of data through a network (the words *data* and *network* are common in both abstracts), the words *communication*, *interface*, *data processing*, *interconnection* appear only in patent A. This explains the difference in proximity score between the two patents.

C Robustness checks – Patent-level results

In this section, first, we study how our measure of *Novelty* and *Proximity* relates to existing measures of patent value, such as the one from Kogan et al. (2017).

Thereafter, we explore to what extent our measure of technological proximity is contaminated by other factors rather than the effective overlap of a patent with the content of a new standard. In this regard, we identify two main concerns.

First of all, our measure could capture more the ability of a firm to lobby and influence the standardization process in order to have patents included in a new standard. If this were the case, our measure would rather capture firms' influence and not the outcome of an independent process. The second concern is about the quality of our patent-to-standard scores and whether they are the result of noise. Both cases represent a potential source of endogeneity that can weaken our empirical identification and our interpretations of the role standards for the diffusion of frontier technologies.

To address the problem of potential lobbying, we conduct two exercises. First, as some firms might participate to technical groups within SSOs, we exclude all firms in years in which they where official members of an SSO. This will make sure that our results are not due to influence or lobbing activity or asymmetric information relative to non-members. Second, another way to indirectly control for lobbying is to exclude al standards by US SSOs, where potential U.S. firms can have more direct influence.

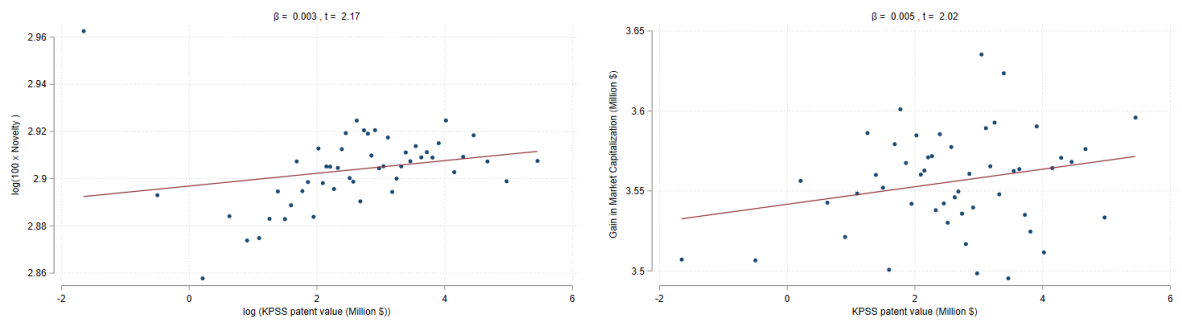
To tackle the issue of miss-measurement and noise, we compute a placebo exercise and show that our measure contains reliable information on the effective proximity of patents to new standards.

Finally, we compare our results of Section 3.2.3 with those from Kogan et al. (2017) and show that our estimates of patent value –obtained by studying market value gains around the patent grant date– are proportional to theirs. Yet, our estimates are three times larger and the difference is proportional to the degree of *novelty* of each patent. This suggests that markets tend to over-valuate novel technologies and that they cannot clearly foresee their diffusion through standards.

C.1 *Novelty*, *Proximity* and patent value from Kogan et al. (2017)

Here we study how the measure of *Novelty* from Kelly et al. (2021), our measure of *Proximity* and the patent value estimated in Kogan et al. (2017) relate to each other. Figure C.1(a) shows that there is a positive and significant correlation between the log of $100 \times$ *Novelty* and the log of the value of the patent (in millions of dollars). In words, patents that represent a bigger discontinuity with the past and are more relevant for future research have higher economic value. Similarly, Figure C.1(b) shows a positive and significant correlation between the log of $100 \times$ *Proximity*[10] and the log of the patent value: patents that better match standards are more valuable.

Figure C.1: NOVELTY, PROXIMITY VS. TRUE PATENT VALUE FROM KOGAN ET AL. (2017)



(a) Novelty vs. KPSS Value

(b) Proximity vs. KPSS Value

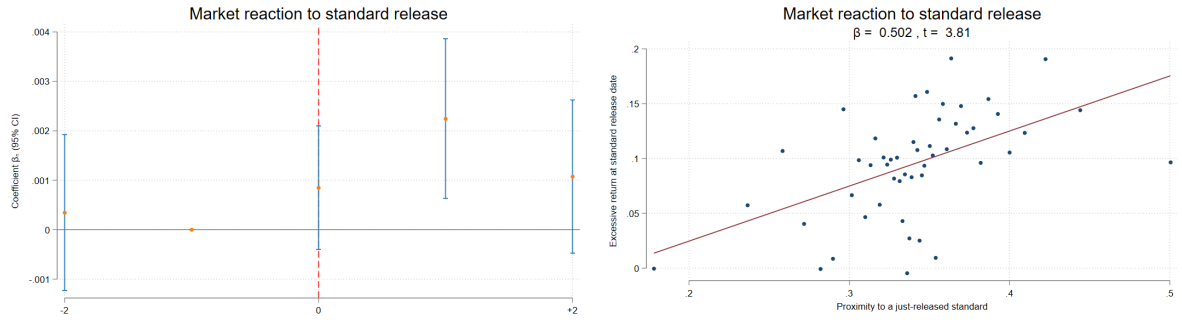
Notes: Figure C.1(a) plots patent's *Novelty* against the true patent value from Kogan et al. (2017). Figure C.1(b) plots patent's *Proximity* against the true patent value.

C.2 Market Reaction and excessive returns – SSOs members excluded

Firms participate in SSOs and their technical committees to gain insight into the standard-setting process. Such involvement can inform R&D strategies and help firms develop capabilities that facilitate compliance with future versions of a standard. When information about SSO activities is publicly available and participation is open to all

[10] As a patent can match multiple standards, here we take the average proximity across all matched standards.

Figure C.2: MARKET REACTION AND EXCESSIVE RETURNS EXCLUDING SSOS MEMBERS



(a) Returns at standard publication date

(b) Returns vs. Proximity

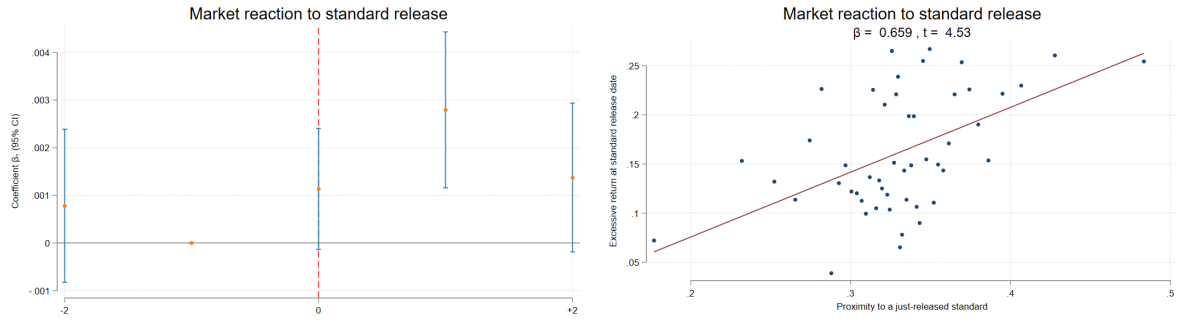
Notes: Figure C.2(a) plot the excessive returns in dates around the release of a new standard when excluding members of US SSOs (see Section 3.2.2 for details). C.2(b) plot the observed excessive returns at standard publication over our *Proximity* measure when excluding members US SSOs.

interested parties, firms compete on equal terms, implying that our proximity measure primarily reflects differences in innovative capability. However, this assumption may not hold if participation entails substantial fixed costs that some firms cannot afford to bear (Fiedler et al., 2023). In that case, the measure may partly capture unequal access to information generated within SSOs.

A further motivation for firms to participate is to promote the inclusion of their patents and technologies in an emerging standard. If inclusion is determined solely by the technical merit of these technologies, the proximity measure remains an appropriate indicator of firms' innovative strengths. By contrast, the measure could be distorted if certain firms are able to secure the adoption of their patents through lobbying or disproportionate influence over the standardization process (see Hall and Ziedonis, 2001; Choi and Gerlach, 2017; Kang and Bekkers, 2015). Nevertheless, it is important to emphasize that SSOs are designed to build standards through broad industry consensus rather than to advance the interests of a small number of participants.

Although it is not possible to determine whether a given standard reflects the selection of the most technically superior innovation or the influence of particular participants, we show that our findings remain robust after controlling for firms' SSO membership. To do so, we use data from Baron and Pohlmann (2018) which reports the name and year of membership of firms when belonging to a SSO from 1996 onwards. Provided with this information, we exclude from our patent-level analysis all the firms in years in which they were members of a SSO and estimate equation (3) of Section 3.2.2 for days around the publication of a new standard. Figure C.2(a) shows that results still hold and the increase in the excessive returns at the date of release of a new standard is relatively bigger than what found originally in Section 3.2.2. Then, with the same data, we estimate equation (5) with $x_{f(i)} = Proximity_{f(i,s)}$, the proximity of patent i –owned by firm f– to standard s. Figure C.2(b) shows that also in this case results hold.

Figure C.3: MARKET REACTION AND EXCESSIVE RETURNS EXCLUDING US-SSOS



(a) Returns at standard publication date

(b) Returns vs. Proximity

Notes: Figure C.3(a) plot the excessive returns in dates around the release of a new standard when excluding standards from US SSOs (see Section 3.2.2 for details). C.3(b) plot the observed excessive returns at standard publication over our *Proximity* measure when excluding standards from US SSOs.

C.3 Market Reaction and excessive returns – US-SSOs standards excluded

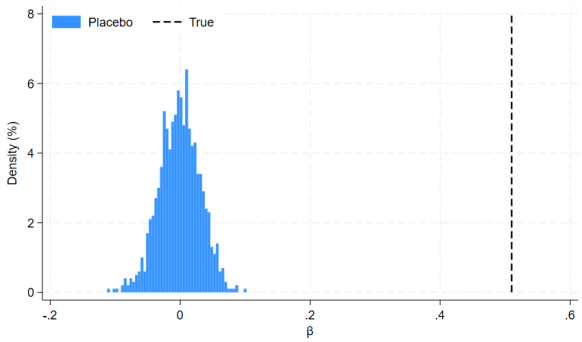
To provide additional evidence against lobbying, we examine the issue using an alternative approach. Standard-setting organizations (SSOs) may operate at either the national level –for example, the US-based American National Standards Institute (ANSI)– or at the international and supranational level, such as the European Committee for Electrotechnical Standardization (CENELEC) and the International Organization for Standardization (ISO). Our underlying assumption is that US firms are likely to exert greater influence within domestic SSOs than within international standard-setting bodies.

Motivated by this distinction, we reconstruct our measures using only patents matched to standards developed by international SSOs, which account for approximately 85% of the standards included in our dataset. Figure C.3(a) and C.3(b) show results when estimating equation (3) and (5). Results still hold and are relatively stronger than what previously estimated in Section 3.2.2.

C.4 Placebo proximity scores at patent level

In this section, we conduct a placebo exercise to assure that our proximity measure is meaningful and to exclude that the results of Section 3.2.2 are driven by noise. To do so, for every patent-to-standard matching score in our dataset, we associate a random value of the variable *Proximity*. Once endowed with this placebo, we estimate equation (5) and store the estimated β-coefficient. We repeat this procedure 1000 times. Finally, we compare the distribution of β from this placebo exercise with the true estimate as reported in Figure 5(b). Figure shows results. For a thousand random draw of the value of *Proximity*, the estimated coefficients have a mean equal to zero. Being the true coefficient equal to 0.5, we conclude that our proximity measure is not random and effectively conveys information on how much a patent is aligned with a new standard.

Figure C.4: MARKET REACTION AND EXCESSIVE RETURNS EXCLUDING US-SSOS



Notes: Figure C.4 plots the distribution of estimates of (5) when the explanatory variable *Proximity* is a random number drawn from a uniform distribution. The plot is based on 1000 draws.

C.5 Comparison of market value gains with the patent value from Kogan et al. (2017)

Here we compare results from Section 3.2.3 with the true value of patents as estimated in Kogan et al. (2017) (KPSS), which exploits the reaction of the stock market at the grant date to filter and extrapolate the true dollar value of a patent. Once matched their patent-level data with ours, we estimate the following equation:

$$Mkt.\ Value\ Gain_{f(i),t+1} = f_{(i)} + \beta Patent\ Value_i^{KPSS} + \epsilon_{f_{(i)},t+1} \tag{C.1}$$

where the dependent variable is the gain in market value –in million dollars– of firm f observed in the stock market after the grant of the patent i at the net of the systematic component, i.e. $Mkt.\ Value\ Gain_{f(i),t+1} = (r_{f_{(i)},t+1} - r_{t+1}^{SP500})Mkt.Value_{f,t}$. $f_{(i)}$ is the firm fixed effect; $Patent\ Value^{KPSS}$ is the value of patent i from Kogan et al. (2017); $\epsilon_{f_{(i)},t+1}$ is the error term. Figure C.5(a) shows that there is a strong and positive relationship between the market value gain and the true patent value from KPSS.

Given this, we proceed by checking if the true value of the patent from KPSS predicts market value gains at the standard release date. To do so, we estimate the following:

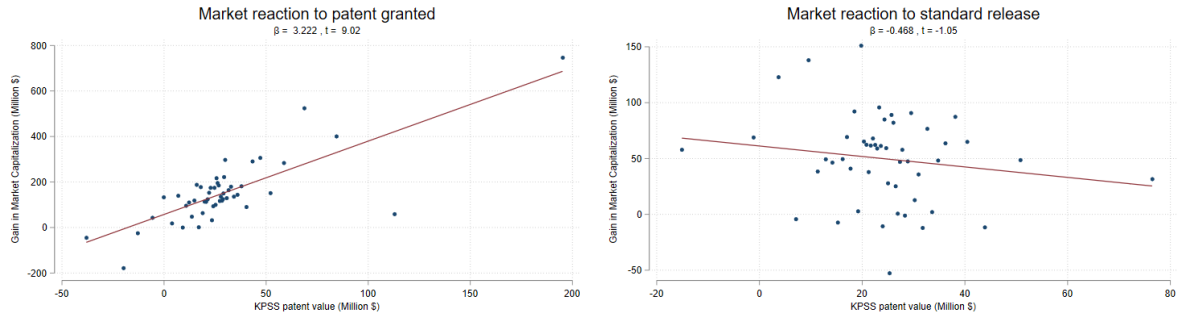
$$Mkt.\ Value\ Gain_{f(i),\tau+1} = f_{(i)} + \theta_s + \beta Patent\ Value_i^{KPSS} + T'_{f(i),\tau}\gamma + \epsilon_{f_{(i)},\tau+1} \tag{C.2}$$

where θ_s is the standard fixed effect and $T'_{f(i)}$ controls for the age of the patent at time τ, the number of patents belonging to firm f and matching the standard s at the moment of its publication τ. Consistent with the results of Section 3.2, the patent value of KPSS does not correlate with the gains observed at the standard release. This corroborates the idea that our measure Proximity conveys information that markets cannot perfectly predict at the grant date of a patent.

As a final analysis, we want to understand to what extent the difference between the market value gain and the true value of the patent from KPSS can be explained by the *novelty* of the patent itself. In order to do so, we consider the following equation:

$$Mkt.\ Value\ Gain_{f(i),t+1} - Patent\ Value_i^{KPSS} = f_{(i)} + \beta Novelty_i + \epsilon_{f_{(i)},t+1}. \tag{C.3}$$

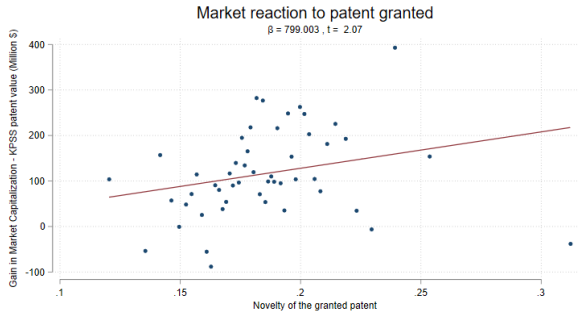
Figure C.5: MARKET VALUE GAINS VS. TRUE PATENT VALUE FROM KOGAN ET AL. (2017)



(a) Mkt. Gains at patent grant vs. KPSS Value (b) Mkt. Gains at standard release vs. KPSS Value

Notes: Figure C.5(a) plots market value gains observed at the patent grant date against the true patent value from Kogan et al. (2017). Figure C.5(b) plots market value gains observed at the standard release date against the true patent value.

Figure C.6: DIFFERENCE IN PATENT VALUATION VS. NOVELTY



Notes: Figure C.6 plots the difference in patent value on the variable *Novelty* as observed at the patent grant date.

Figure C.6 shows that that markets tend to valuate more novel innovations beyond their true value. Such difference is larger the more novel is the invention.

D Robustness checks – Firm-level results

In this section, we check if the firm-level aggregated measure of technological proximity (Tech.Proximity) is contaminated by other factors that can bias our results and interpretations. Keeping in mind the same concerns discussed in Appendix C, we proceed as follows.

To address the concern of potential lobbying activity, we estimate results of Section 4.2 by controlling for the membership of firms to SSOs over time. Then, as a second test, we construct the firm-level measure *Tech.Proximity* by considering only matches of patents with international standards, i.e. we exclude standards from American SSOs in the computation of scores and their aggregation.

To address concerns of miss measurement, we re-estimate results through a placebo exercise and show that –also when aggregating at the firm level– our measure of technological proximity is meaningful. Moreover, we show also that it does not depend from the stock of patents issued by the firm or the most recent granted patents, but

actually by the quality of matches. To corroborate even further this point, for each standard we consider the three best matches and show that it is not the quantity of matching patents (which on average have a score equal to zero) but the few matching well a standard that drive results.

Finally, we show that prior to the release of either a patent or a standard, firms do not differ significantly in terms of observables.

D.1 Controlling for SSOs membership

In light of the discussion in Appendix C.2 on lobbying activity and SSOs membership, here we augment equation (6) as follows:

$$\log(Y)_{f,t} = \sum_{n=-8}^{N=T} \beta_n \textit{Tech.Novelty}_{f,t-n} + \sum_{n=-8}^{N=T} [\gamma_n \textit{Tech.Proximity}_{f,t-n} + \eta_n \textit{Member}_{f,t-n}] + \alpha_{f,t}\phi_{s(f),t} + X'_{f,t-1}\eta + \varepsilon_{f,t} \quad \text{(C.4)}$$

where *Member* $= 1$ if the firm f was a member of an SSO during the same year and/or two years prior to the release of a standard.

Figure C.9 shows results when the dependent variable Y is the market value of the firm. Under this robustness check, the results of Section 4.2 still hold: both innovation and diffusion margins matter for the market value of the firm, and the effect is proportional to the level of *Tech.Novelty* and *Tech.Proximity*. Figure C.10 shows results when the dependent variable Y is the book value of the firm. Also in this case, results hold.

D.2 Excluding US-SSOs standards from aggregation

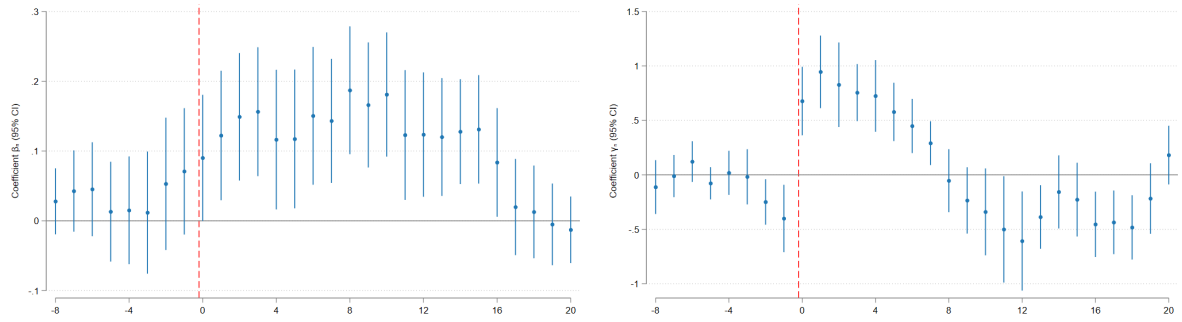
To further address the concern of potential lobbying activity, here we build the variable *Tech.Proximity* by excluding all standards issued by American SSOs, where potentially US corporations can have bigger influence. Given this restriction, we then estimate equation (6). Figure C.9 and C.10 show results respectively when the dependent variable is the market value and the book value of the firm. Also in this case, the results of Section 4.2 hold true.

D.3 The role of patent portfolio size and strategic patenting activity

In this section, we check if our measure of *Tech.Proximity* is a byproduct of the size of the patent portfolio. In fact, it could be the case that this firm-level measure reflects the number of patents in the portfolio rather than the quality of matches of those patents with a standard. In light of this, we augment equation (6) as follows:

$$\log(Y)_{f,t} = \sum_{n=-8}^{N=T} \beta_n \textit{Tech.Novelty}_{f,t-n} + \sum_{n=-8}^{N=T} [\gamma_n \textit{Tech.Proximity}_{f,t-n} + \eta_n \textit{Ptf.Size}_{f,t-n}] + \alpha_{f,t}\phi_{s(f),t} + X'_{f,t-1}\eta + \varepsilon_{f,t} \quad \text{(C.5)}$$

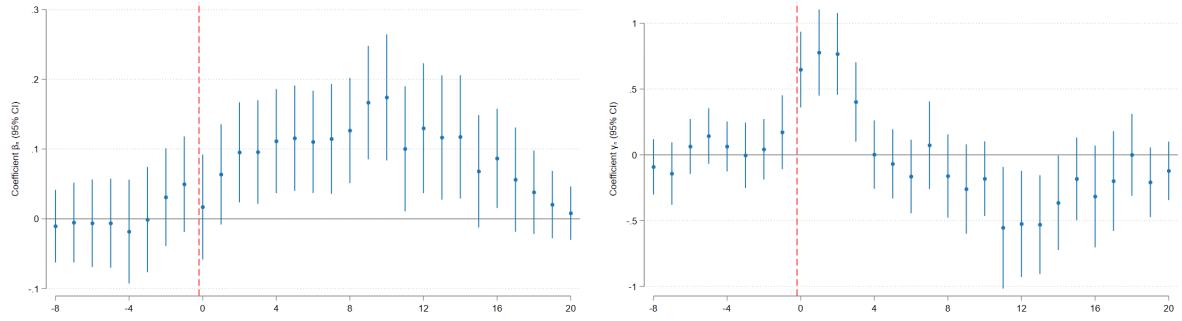
Figure C.7: INNOVATION, STANDARDIZATION AND THE MARKET VALUE OF THE FIRM



(a) Novelty (b) Proximity

Notes: Figure C.9(a) and C.9(b) plot the estimated coefficients β_n and γ_n. The dependent variable is the log-level of the market value of the firm. In both figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are clustered at the firm-level. The red-dashed line indicates respectively the grant date of a patent and the publication date of the standard.

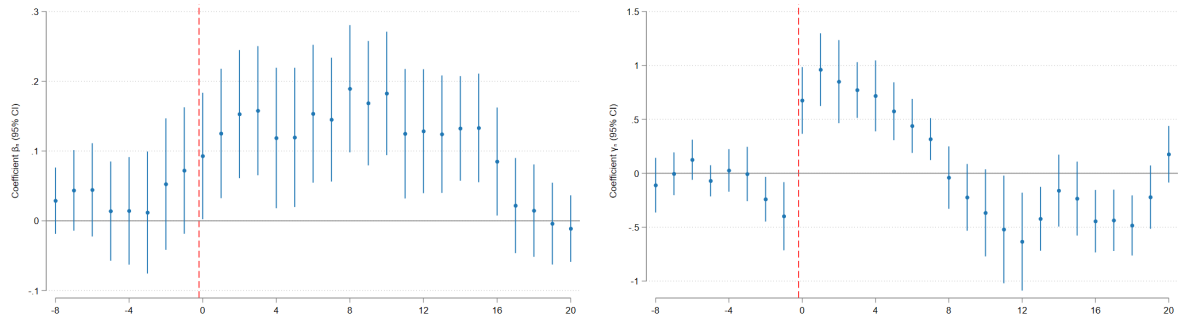
Figure C.8: INNOVATION, STANDARDIZATION AND THE BOOK VALUE OF THE FIRM



(a) Novelty (b) Proximity

Notes: Figure C.10(a) and C.10(b) plot the estimated coefficients β_n and γ_n. The dependent variable is the log-level of the book value of the firm. In both figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are clustered at the firm-level. The red-dashed line indicates respectively the grant date of a patent and the publication date of the standard.

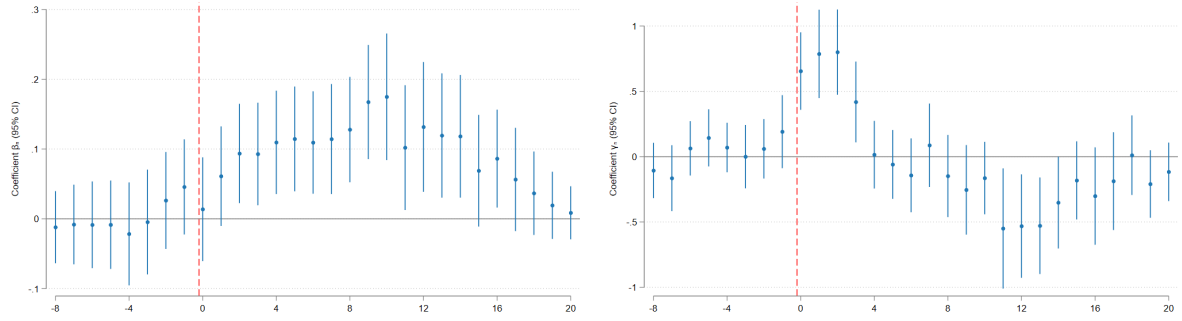
Figure C.9: INNOVATION, STANDARDIZATION AND THE MARKET VALUE OF THE FIRM



(a) Novelty (b) Proximity

Notes: Figure C.9(a) and C.9(b) plot the estimated coefficients β_n and γ_n. The dependent variable is the log-level of the market value of the firm. In both figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are clustered at the firm-level. The red-dashed line indicates respectively the grant date of a patent and the publication date of the standard.

Figure C.10: INNOVATION, STANDARDIZATION AND THE BOOK VALUE OF THE FIRM



(a) Novelty (b) Proximity

Notes: Figure C.10(a) and C.10(b) plot the estimated coefficients β_n and γ_n. In both figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are clustered at the firm-level. The red-dashed line indicates respectively the grant date of a patent and the publication date of the standard.

where *Ptf.Size* is the log of the number of patents in the portfolio of firm f. Figure C.11 shows results when the dependent variable Y is the market value of the firm. Under this robustness check, the results of Section 4.2 still hold: both innovation and diffusion margins matter for the market value of the firm, and the effect is proportional to the level of *Tech.Novelty* and *Tech.Proximity* despite the size of the patent portfolio at the moment of the standard issuance. Figure C.12 shows results when the dependent variable Y is the book value of the firm. Also in this case, results hold.[11]

Finally, we also control for strategic patenting activity. In fact, in case of information leakages, firms might abnormally issue patents matching a new standard just before the standard's release. To control for this, we augment

$$\log(Y)_{f,t} = \sum_{n=-8}^{N=T} \beta_n Tech.Novelty_{f,t-n} + \sum_{n=-8}^{N=T} [\gamma_n Tech.Proximity_{f,t-n} + \eta_n NewPatents_{f,t-n}] + \alpha_{f,t}\phi_{s(f),t} + X'_{f,t-1}\eta + \varepsilon_{f,t} \quad \text{(C.6)}$$

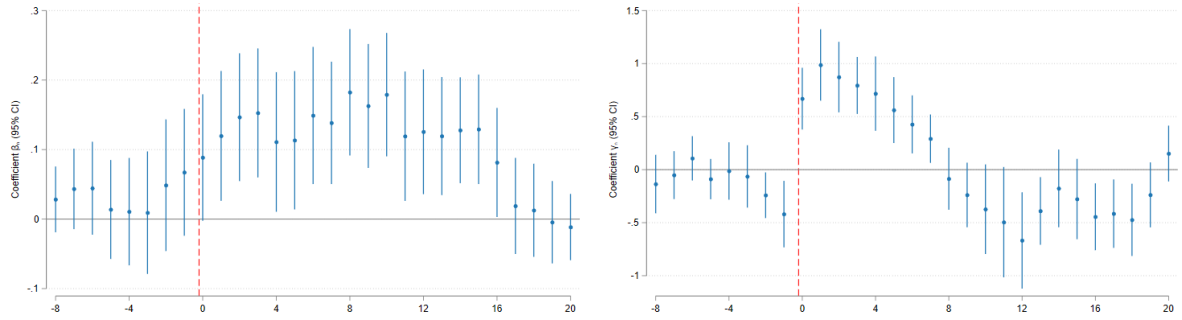
where *NewPatents* is the flow of new patents granted to firm f in the year just before the release of a standard. Figure C.13 shows results when the dependent variable Y is the market value of the firm. Under this robustness check, the results of Section 4.2 still hold: both innovation and diffusion margins matter for the market value of the firm, and the effect is proportional to the level of *Tech.Novelty* and *Tech.Proximity* despite the size of the flow of new patents granted in the year just before the standard. Figure C.14 shows results when the dependent variable Y is the book value of the firm. Also in this case, results hold.[12]

D.4 *Tech.Proximity* built considering best matches only

If in the previous robustness checks we show that it is not the size of the patent portfolio that matters, here we show that results are indeed driven by the few large patent-to-standard scores that are detected by our matching algorithm. As discussed in Section 3.1, most of our patent-to-standard matches are zero or very close to zero. Within standard and firm, there are only few large positive matches. In this section we show that these are the matches that matter for our results. To do so, differently from what done in Section 4.1, we build *Tech.Proximity* as the *mean* of the three best patent matching a standard. Once endowed with this metric, we estimate equation (6). Figure C.15 shows results when the dependent variable Y is the market value of the firm. Under this robustness check, the results of Section 4.2 still hold: both innovation and diffusion margins matter for the market value of the firm. Figure C.16 shows results when the dependent variable Y is the book value of the firm. Also in this case, results hold.

[11] Both sets of results hold whether we consider the log or the level of the portfolio size.
[12] Both sets of results hold whether we consider the log or the level of the flow of newly granted patents.

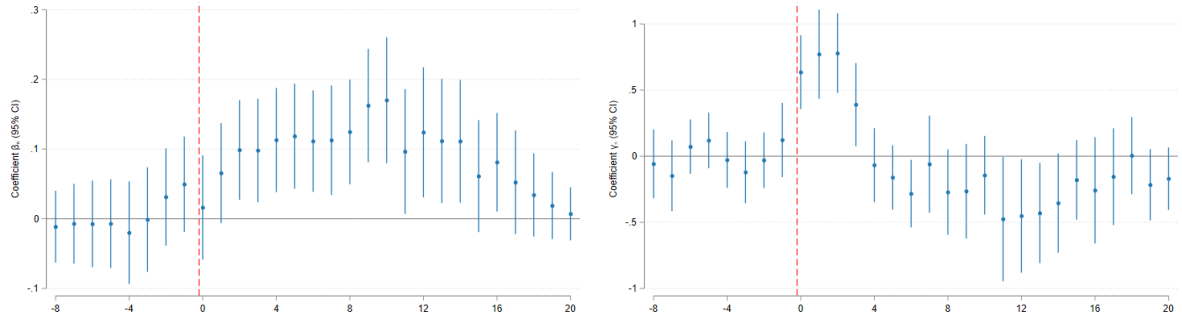
Figure C.11: INNOVATION, STANDARDIZATION AND THE MARKET VALUE OF THE FIRM



(a) Novelty (b) Proximity

Notes: Figure C.11(a) and C.11(b) plot the estimated coefficients β_n and γ_n. The dependent variable is the log-level of the market value of the firm. In both figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are clustered at the firm-level. The red-dashed line indicates respectively the grant date of a patent and the publication date of the standard.

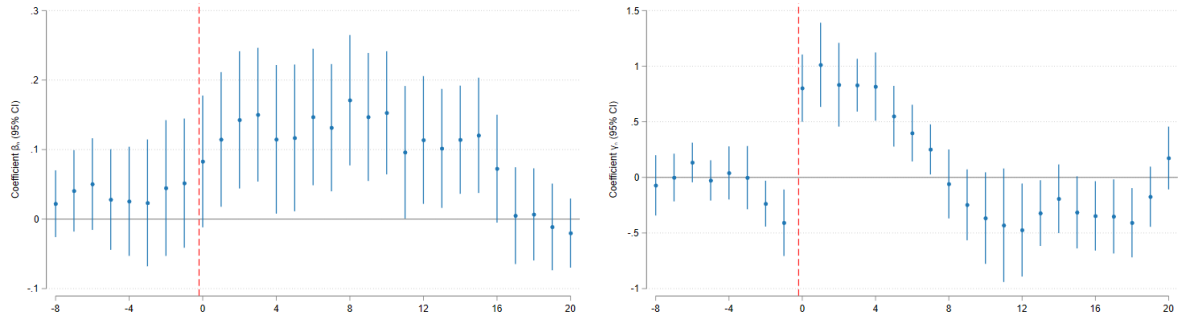
Figure C.12: INNOVATION, STANDARDIZATION AND THE BOOK VALUE OF THE FIRM



(a) Novelty (b) Proximity

Notes: Figure C.12(a) and C.12(b) plot the estimated coefficients β_n and γ_n. The dependent variable is the log-level of the book value of the firm. In both figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are clustered at the firm-level. The red-dashed line indicates respectively the grant date of a patent and the publication date of the standard.

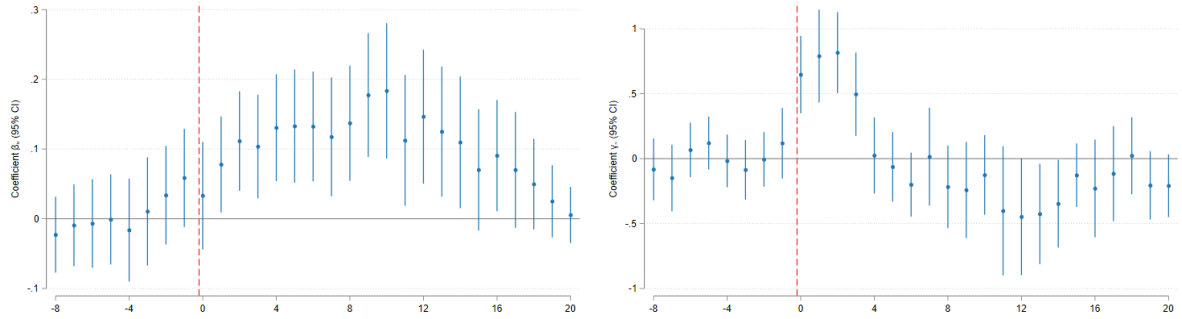
Figure C.13: INNOVATION, STANDARDIZATION AND THE MARKET VALUE OF THE FIRM



(a) Novelty (b) Proximity

Notes: Figure C.13(a) and C.13(b) plot the estimated coefficients β_n and γ_n. The dependent variable is the log-level of the market value of the firm. In both figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are clustered at the firm-level. The red-dashed line indicates respectively the grant date of a patent and the publication date of the standard.

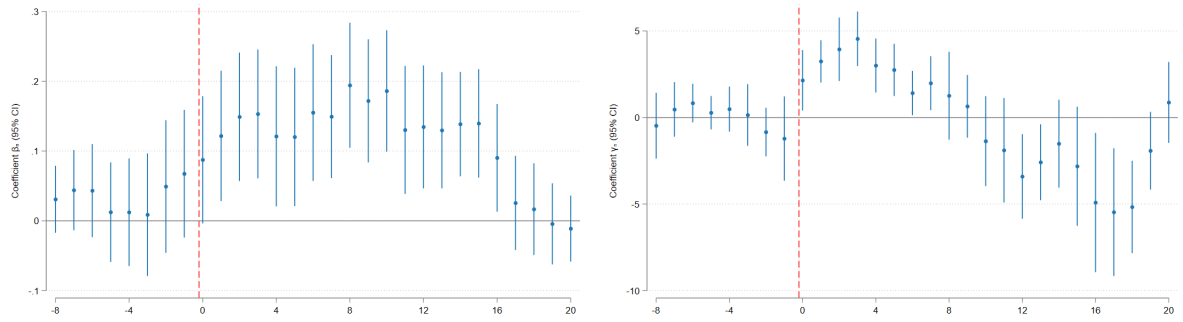
Figure C.14: INNOVATION, STANDARDIZATION AND THE BOOK VALUE OF THE FIRM



(a) Novelty (b) Proximity

Notes: Figure C.14(a) and C.14(b) plot the estimated coefficients β_n and γ_n. The dependent variable is the log-level of the book value of the firm. In both figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are clustered at the firm-level. The red-dashed line indicates respectively the grant date of a patent and the publication date of the standard.

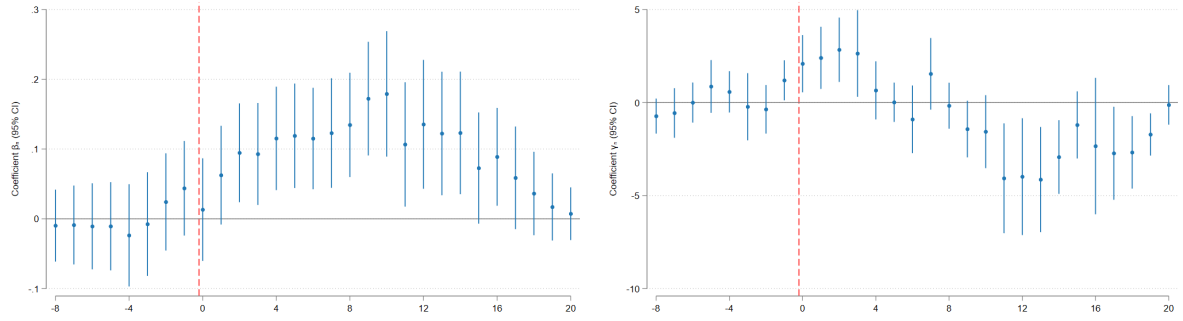
Figure C.15: INNOVATION, STANDARDIZATION AND THE MARKET VALUE OF THE FIRM



(a) Novelty (b) Proximity

Notes: Figure C.15(a) and C.15(b) plot the estimated coefficients β_n and γ_n. The dependent variable is the log-level of the market value of the firm. In both figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are clustered at the firm-level. The red-dashed line indicates respectively the grant date of a patent and the publication date of the standard.

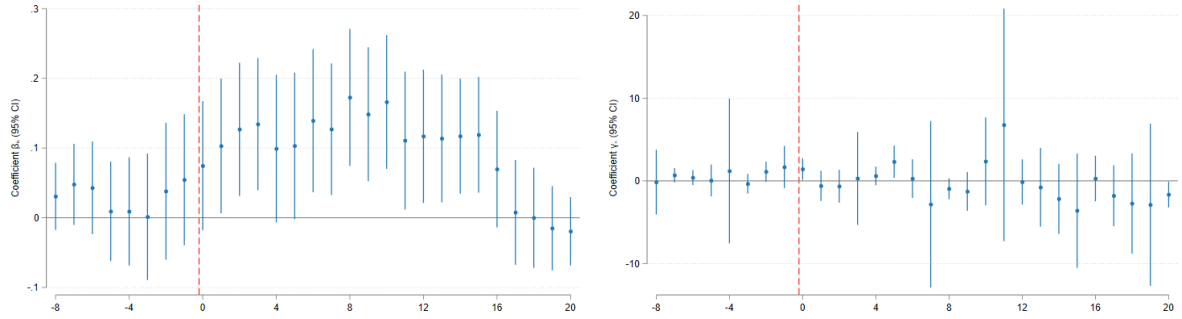
Figure C.16: INNOVATION, STANDARDIZATION AND THE BOOK VALUE OF THE FIRM



(a) Novelty (b) Proximity

Notes: Figure C.16(a) and C.16(b) plot the estimated coefficients β_n and γ_n. The dependent variable is the log-level of the book value of the firm. In both figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are clustered at the firm-level. The red-dashed line indicates respectively the grant date of a patent and the publication date of the standard.

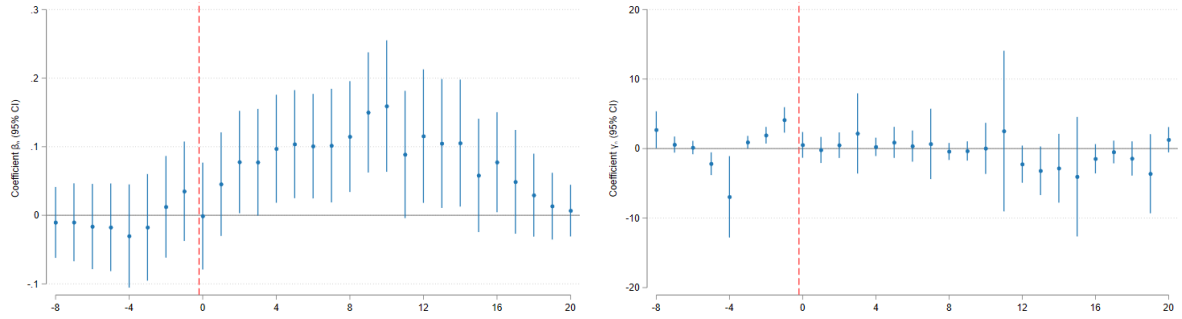
Figure C.17: INNOVATION, STANDARDIZATION AND THE MARKET VALUE OF THE FIRM



(a) Novelty (b) Proximity

Notes: Figure C.17(a) and C.17(b) plot the estimated coefficients β_n and γ_n. The dependent variable is the log-level of the market value of the firm. In both figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are clustered at the firm-level. The red-dashed line indicates respectively the grant date of a patent and the publication date of the standard.

Figure C.18: INNOVATION, STANDARDIZATION AND THE BOOK VALUE OF THE FIRM



(a) Novelty (b) Proximity

Notes: Figure C.18(a) and C.18(b) plot the estimated coefficients β_n and γ_n. The dependent variable is the log-level of the book value of the firm. In both figures, the 95% confidence intervals for each point-estimate is reported. Standard errors are clustered at the firm-level. The red-dashed line indicates respectively the grant date of a patent and the publication date of the standard.

D.5 Placebo proximity at firm level

In this section, we corroborate the validity of our measure of technological proximity through a placebo exercise. Similarly to Appendix C.4, we associate a random draw for every patent-to-standard match and build the variable *Tech.Proximity* according to the definition presented in Section 4.1. We repeat this procedure 1000 times, and take the average value of *Tech.Proximity* across all iterations. Once endowed with this placebo measure of technological proximity at the firm level, we estimate equation(6) when the dependent variable is either the log of the market value or the book value of the firm. Figure C.17 and C.18 show that there is no significant effect of the placebo version of our *Tech.Proximity* on the dependent variable.

Table C.1: DIFFERENCES IN FIRM-LEVEL CHARACTERISTICS

	(1) Tobin's Q	(2) Leverage	(3) Mkt.Cap	(4) ROE	(5) PE	(6) Size	(7) Age	(8) Patent Flow	(9) Patent Stock
I(*Tech.Prox.>0*)	-0.00132	-0.00112	0.00692	0.0125	6.079	-0.000440	4.25e-15	0.000308	-0.000253
	(-0.17)	(-0.90)	(1.09)	(1.27)	(0.78)	(-0.20)	(1.64)	(1.20)	(-0.76)
I(*Tech.Novelty>0*)	0.0122	-0.00127	0.00280	0.00204	1.927	-0.00320	-3.09e-15	-0.000381	-0.000295
	(1.49)	(-1.39)	(0.67)	(1.24)	(0.26)	(-1.63)	(-1.28)	(-1.83)	(-1.32)
N	16210	16279	16237	16236	16204	16279	16279	16279	16279
Time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Return-on-equity (ROE) is defined as the ratio of the firms' quarterly income over the value of equity. PE is the price-earning ratio. Size is the logarithm of the value of the assets of the firm. The variable *Stock of Patent* corresponds to the number of patents accumulated until that quarter and normalized by the average value of fixed assets. The variable *New Patent* corresponds to the number of patents released during the quarter and normalized by the average value of fixed assets. All other dependent variables (Age, Q, Leverage, Market Cap.) and dummy variable $\mathbb{I}[\texttt{Tech.Prox} > 0]$ are define in Section 4.1. t-statistics are reported in parenthesis. Standard errors are clustered at the firm level. "*", "**" and "***" designate significance at the 1%, 5% and 10% level.

D.6 Differences across "treated" and "untreated" firms before patent grant and standard release

In this section, we study whether there are significant (pre-grant and pre-standardization) differences across firms that do receive positive values of Tech.Novelty and Tech.Proximityy and those that do not. To do so, we run the following regression:

$$Y_{f,t-4} = \beta \mathbb{I}[\texttt{Tech.Novelty}_{f,t} > 0] + \gamma \mathbb{I}[\texttt{Tech.Proximity}_{f,t} > 0] + \alpha_{f,t} + \phi_{s(f),t} + \varepsilon_{f,t}$$

where $Y_{f,t}$ can be either: Tobin's Q, leverage, log of market capitalization, return-on-equity (ROE), price-earning ratio (PE), , size (log of assets), age, the number of new patents issued and the stock of patents (both normalized by the average value of fixed assets). All variables are observed at $t-4$. $\alpha_{f,t}$, $\phi_{s(f),t}$ are respectively firm and NAICS3 industry interacted with a year and a quarter time dummy.

As shown in Table C.1, one year before the release of the standard, firms with a positive novelty or proximity values did not significantly differ from firms with either zero novelty or proximity in these several dimensions. In particular, we want to highlight the fact that firms that have issued more patents just before the standard release are not more likely to receive a positive value for Tech.Proximity (column 8). Similarly, firms that have accumulated over time a larger portfolio of patents are not more likely to register positive values for Tech.Proximity (column 9). This suggests that innovation activity at the extensive margin cannot explain our measure of technological proximity and that the strategic release of patents just before the publication of the standard is not present in the data. If we study differences in observables at $t-5$, ..., $t-8$ across firms that do receive positive values of Tech.Novelty and Tech.Proximity today and those that do not, no significant result is found. This exercise is available upon request to the authors.